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Job Creation in Development Finance Institution (DFI) Investments: Firm-level Determinants and Effect of DFI funding

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Abstract

This paper is concerned with the job creation dynamic of development finance institutions' (DFI) investments and approaches the topic from two perspectives. Firstly, it reviews the key determinants of firm-level employment growth from general economic literature and examines how they explain job creation in DFI investments. Secondly and more interestingly, the effect of DFI funding itself on firm-level employment growth is examined.

Utilizing a unique firm-level dataset of 239 DFI investments of Finnfund (Finnish Fund for Industrial Cooperation Ltd), Finland's primary DFI, during the years 2008 to 2014, this study finds several interesting results. Examining how determinants of employment growth from general economic literature explain employment growth in DFI investments, a strong negative relationship of both firm size and capital intensity with employment growth is established. This result is in line with previous literature on the relationship between firm size and employment growth and with the Cobb-Douglas relationship respectively, but has not been previously empirically tested with a sample of DFI portfolio firms. More interestingly, when controlling for firm size and capital intensity, no statistically significant relationship between returns of DFI investments and firm-level employment growth is found. This parts from previous findings of DFI practitioner literature, suggesting potential lack of methodological rigor in these studies.

Secondly, additional DFI funding is found to positively and statistically significantly effect firm-level employment growth in sample firms. By matching 96 Finnfund investments that received additional funding during the years 2008 to 2014 with a group of control investments not receiving additional funding through a propensity score matching (PSM) procedure, a statistically positive effect of additional funding on average annual employment growth is established. This is the first paper to document such a micro-level relationship between DFI funding and firm-level job creation. While the employment effect does not statistically persist in one of the matched comparisons and the robustness analysis using a DID-PSM approach yields mixed results, general direction and magnitude of the observed effect strongly suggests that additional DFI funding has a positive effect on firm-level job creation. Considering that the positive effect of DFI funding on employment growth is observed as an increase in the rate of employment growth, not mere increase in number of employees, and is observable already within the same year of funding, non-financial benefits of DFI funding could have a big role in explaining the observed effect.

Keywords Development finance institutions, development finance, firm-level employment growth, employment growth determinants, job creation, firm size, firm age, firm capital intensity

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Työn nimi Työllisyyskasvun yritystason tekijät kehitysrahoitusyhtiöiden sijoituksissa ja kehitysrahoitusyhtiöiden rahoituksen työllistämisvaikutus

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Tiivistelmä

Tutkielma pyrkii selvittämään työpaikkojen luomista kehitysrahoitusyhtiöiden sijoituskohteissa ja keskittyy tarkastelemaan asiaa kahdelta kantilta. Ensiksi työ käy läpi lähdekirjallisuuden määrittelemät tärkeimmät, yrityskohtaisen työllisyyskasvun tekijät ja tarkastelee näiden tekijöiden suhdetta työllisyyskasvuun kehitysrahoitusyhtiöiden sijoituskohteissa. Toiseksi, työ tutkii kehitysrahoitusyhtiöiden rahoituksen vaikutusta yritystason työllisyyskasvuun.

Tutkimuksen aineistona käytetään ainutlaatuista, yritystason aineistoa joka kattaa 239 Finnfundin (Teollisen Yhteistyön Rahasto Oy:n), Suomen suurimman kehitysrahoitusyhtiön, sijoituskohdetta vuosilta 2008 – 2014. Ensimmäiseksi, tarkasteltaessa työllisyyskasvun tekijöitä aineiston yrityksissä, sekä yrityksen koolla, että yrityksen pääomaintensiteetillä havaitaan vahva negatiivinen suhde työllisyyskasvun kanssa. Tulos on johdonmukainen aihepiirin lähdekirjallisuuden kanssa, mutta tekijöiden välistä suhdetta ei ole ennen empiirisesti tutkittu kehitysrahoitusyhtiöiden sijoituskohteissa. Lisäksi, kun yrityksen koko ja pääomaintensiteetti lisätään regressiomalliin kontrollimuuttujina, kehitysrahoitusyhtiöiden sijoituskohteiden sijoitustuotto menettää aikaisemmissa tutkimuksissa löydetyn tilastollisen merkittävyytensä sijoituskohteiden työllisyyskasvua selittävänä tekijänä. Tämä tulos kyseenalaistaa aihepiiriin liittyvien aikaisempien tutkimuslöydösten tutkimusmenetelmällistä oikeaoppisuutta.

Työn toinen ja mielenkiintoisempi tutkimuslöydös on, että kehitysrahoitusyhtiön lisärahoituksella ja yritystason työllisyyskasvulla on tilastollisesti merkittävä, positiivinen suhde. Keskimääräinen työlliskasvu on merkittävästi korkeampi aineiston 96:lla yrityksellä, jotka saivat vuosina 2008 – 2014 lisärahoitusta Finnfundilta, kuin vertailuryhmän yrityksillä, jotka eivät saaneet lisärahoitusta kyseisellä ajanjaksolla. Sopiva vertailuryhmä lisärahoitusta saaneille yrityksille luodaan Propensity Score Matching (PSM) –menetelmällä, käyttäen saman aineiston yrityksiä. Vaikkakin yhden vertailuryhmän kohdalla yritystason työllisyyskasvun ero ei ole tilastollisesti merkittävä ja tulosten robustisuusanalyysi hyödyntäen DID-PSM –menetelmää voidaan tulkita tuloksettomaksi, tilastollisen suhteen suuruusluokka ja positiivinen etumerkki, jotka ovat havaittavissa kaikissa suoritetuissa analyyseissä, viittaavat vahvasti siihen, että kehitysrahoitusyhtiön lisärahoituksella on positiivinen vaikutus yritystason työllisyyskasvuun. Lisärahoituksen vaikutus työlliskasvuun havaitaan suhteellisena yritystason työllisyyskasvuna, eikä pelkkänä työntekijöiden määrän kasvuna ja vaikutus on havaittavissa saman vuoden sisällä lisärahoituksesta. Tähän pohjautuen, vaikuttaa todennäköiseltä, että kehitysrahoitusyhtiöiden rahoitukseen liittyvät ei-taloudelliset hyödyt selittävät suuriltaosin havaittua suhdetta.

Avainsanat Kehitysrahoitusyhtiöt, kehitysrahoitus, yritystason työllisyyskasvu, työllisyyskasvun tekijät, työpaikkojen luominen, yrityksen koko, yrityksen ikä, yrityksen pääomaintensiteetti

Contents

1. Introduction

1.1 Background and motivation

Development finance institutions (DFIs) are rapidly becoming one of the key channels for developed countries to subsidize and support economic development of developing countries (see e.g. Te Velde and Massa, 2011). DFIs are specialized development banks or subsidiaries mandated and supported by their governments to promote economically, environmentally and socially sustainable development in developing countries through financing and investing in profitable private sector enterprises. They are usually majority-owned by national governments and source their capital from national or international development funds or benefit from government guarantees.

Given their development mandate, when managing their investment portfolios, DFIs are constantly evaluating potential investment opportunities across two key criteria: i) potential financial returns on investment and ii) potential development impact of the investment.

In order to better track the success of their development mission, DFIs have started in increasing manner to measure development effects of their investments as quantifiable development impact metrics – these include e.g. number of jobs created by their investee firms, as well as the trade balance and tax revenue effect of investee firms in their domestic economies (Te Velde and Massa, 2011 and Joujean and te Velde, 2013). However, while there is ample academic literature on investment-level determinants of financial returns in different asset classes, to help guide DFI investment managers when choosing their investment targets, there exists no academic literature on investment-level determinants of the different development effects. As an optimal DFI investment portfolio would maximize both the financial return and the development impact of the portfolio, information on determinants of development impact is critical for DFI fund managers when deciding on where to channel their investments.

This study aims to fill this vacuum by focusing on job creation impact of DFI investments. Job creation is focused on for two reasons. Firstly, it is considered as one of the main development challenges currently faced by low income countries (Jouanjean and te Velde, 2013) and secondly, it is one of the most consistently tracked development impacts of DFIs, thus offering data of sufficient quality and quantity for an empirical analysis.

This paper approaches the job creation impact of DFI investments from two perspectives. Firstly, it reviews the key determinants of firm-level employment growth from general economic literature and examines their relationship with job creation in DFI investments. Secondly and more interestingly, the effect of DFI funding itself on firm-level employment growth is examined. This effect has not yet been examined by empirical literature and is interesting from at least two standpoints. Firstly, such an analysis can yield interesting insights to both DFI professionals and firms receiving DFI investments, to help improve their future operations. Secondly for policymakers working with economic development and interested in policies specifically pursuing employment growth, such an analysis provides an indication of whether supporting DFI activity is an efficient way for possibly achieving desired policy outcomes.

1.2 Research problem and purpose

According to Massa (2011), since the year 2005 an increasing number of DFIs have assessed the results of their investment operations by means of Development Outcome Tracking System (DOTS). DOTS measures impacts of DFI operations against a set of indicators classifiable into four categories: financial performance (e.g. ROI, ROIC and project cost), economic performance (e.g. contributions to target country's employment and tax revenues), environmental and social performance (e.g. number occupational injuries, water and energy consumption, etc.) and private sector development (e.g. SMEs reached). While the past decade has seen such notable increases in both impact measurement and assessments of the activities of DFIs at macro levels (e.g. Te Velde and Massa, 2011 and Joujean and te Velde, 2013), there is however still very little evidence on empirical relationships of DFI job creation on micro-level (Joujean and te Velde, 2013).

There is an extensive field of economic literature focused on firm-level employment growth determinants (see Section 2.1 for more details) and some attempts have been made to examine these relationships also in the context of DFI investee firms (e.g. IFC, 2007 and Wilton and Allen, 2012). However, there are two key problems related to the currently available literature on micro-level determinants of job creation in DFI investments. Firstly, as indicated by firm characteristics of the sample firms analyzed in this paper, it seems likely that DFI investee firms are on average quite different from the average firm in general firm population of developing countries (see Section 4.2 for more details). This potentially questions the generalizability of findings from general employment growth determinant literature on DFIs. Secondly, while explicit literature on job creation in DFI investments (IFC, 2007 and Wilton and Allen, 2012) improves our understanding of the topic with its relevant sample focus, these papers lack some of the control variables and other methodological rigor present in peer-reviewed literature focusing on employment growth determinants of firms more generally (e.g. Haltiwanger et al., 2013 and Rijkers et al., 2014). Thus, there is a clear need for a more scientific approach in examining firm-level employment growth determinants in DFI investments.

Also and more interestingly, relationship between DFI funding and job creation has not been examined at micro-level by any prior literature. This is striking, considering that as mentioned by Massa (2011), contributions to target country's employment has been a key performance metric for DFI investments since year 2005. In order words, whilst DFIs often report and even boast on the number of jobs their investee firms have created, no study has critically examined the counterfactual of how job creation of investee firms would have developed had a DFI never invested in such firms.

Utilizing a unique, firm-level dataset of 239 DFI investments of Finnfund (Finnish Fund for Industrial Cooperation Ltd), Finland's primary DFI, during the years 2008 to 2014, this study aims to fill the previously outlined vacuum in empirical DFI literature. Firstly, this paper examines whether firm size, age and capital intensity are associated with employment growth in DFI investments in a similar manner as predicted by general firm-level employment growth literature (e.g. Cobb and Douglas, 1928, Davis, 1992, Haltiwanger et al., 2013 and Rijkers et al., 2014). The study will also examine the relationship between returns of DFI investments and firm-level employment growth, while controlling for these established employment growth determinants of general economic literature.

Secondly, this paper looks at whether additional DFI funding received by 96 sample firms had an effect on employment growth of these firms during the sample years. The employment effect of additional DFI funding is examined by comparing average employment growth of sample firms receiving additional funding during a given year against propensity score matched (PSM) control firms from the same Finnfund sample that did not receive such funding. Examining the effect of additional funding on funded firms against characteristically similar DFI firms that were not funded, allows to make inferences of causal nature on the relationship between additional DFI funding and firm-level employment growth.

1.3 Contribution to existing literature

This paper adds to existing literature on two fronts. Firstly, it looks at how determinants of employment growth that have cemented their place in general economic literature, namely firm size, age and capital intensity explain employment growth in DFI investments. Determinants of employment growth in DFI investments have not been previously studied with similar methodological rigor as determinants of employment growth in the general firm population (see e.g. Haltiwanger et al., 2013 and Rijkers et al., 2014). This is striking, considering that DFIs are the subcategory of investors to whom job creation of their investee firms is of specific interest. Also, extending this analysis, the relationship between DFI investments' returns and job creation is examined for the first time when controlling for firm size, age and capital intensity.

Secondly and more interestingly, firm-level effect of DFI funding on employment growth is examined. This fills a vacuum in DFI related literature, where the impact of DFI funding on employment growth has to date only been studied at a macro-level (Massa, 2011, and Joujean and te Velde, 2013).

1.4 Key findings

Firstly, examining how determinants of employment growth from general economic literature explain employment growth in DFI investments, several interesting relationships are established. This paper finds a strong negative relationship of both firm size and capital intensity with firm-level employment growth in DFI investments. This result is in line with Haltiwanger et al. (2013) and Rijkers et al. (2014) on firm size and with the Cobb-Douglas relationship (Cobb and Douglas, 1928) on firm capital intensity. However, unlike Haltiwanger etl al. (2013) and Rijkers et al. (2014), this paper finds no statistically significant relationship between firm age and employment growth. Also when controlling for firm size and capital intensity, no statistically significant relationship between returns of DFI investments and firm-level employment growth is observed. This parts from previous findings of DFI practitioner literature, which not controlling for these well-established determinants of firm-level employment growth has found a positive relationship between DFI investment returns and investment-level job creation (Wilton and Allen, 2012).

Secondly, additional DFI funding is found to positively and statistically significantly effect firm-level employment growth in sample firms. By matching 96 Finnfund investments that received additional funding during the years 2008 to 2014 with a group of control investments not receiving additional funding through a PSM procedure, a statistically positive effect of additional funding on average annual employment growth is established. This is the first paper to document such a micro-level relationship between DFI funding and firm-level job creation. While the employment effect does not statistically persist in one of the matched comparisons and the robustness analysis using a DID-PSM approach (following Imai and Azam, 2012) yields mixed results, general direction and magnitude of the observed effect strongly suggests that additional DFI funding has a positive effect on firm-level job creation. Considering that the positive effect of DFI funding on employment growth is observed as an increase in the rate of employment growth, not mere increase in number of employees, and is observable already within the same year of funding, non-financial benefits of DFI funding could have a big role in explaining the observed effect. The findings leave space for interesting further research on whether DFI funding has a positive employment effect also on firms previously not backed by DFIs and how can financial and non-financial benefits of DFI funding potentially explain the observed effect.

1.5 Limitations of the study

Due to the novelty of the research topic and issues related to study design, this paper has several limitations that must be bared in mind when interpreting the results. First limitation concerns generalizability of the findings, as the study uses a sample of portfolio firms from only one development finance institution, Finnfund. As reviewed by Kingombe et al. (2011), there are significant differences across practices and activities of different DFIs and thus findings that apply in the context of one DFI may not apply for all DFIs.

Secondly, the study does not take a stand on the debate of whether government subsidies and funds of “socially responsible” investors should be channeled into investments that foster employment growth in the first place. In other words, job creation is assumed in this study to be a desired outcome of DFI investment activity, but no stand is taken on whether such job creation is actually socioeconomically beneficial or whether it even should be a desired investment outcome. For instance, there is a wide debate on how not only quantity, but also quality of jobs created is developing countries is highly important (see e.g. Veldhuis et al., 2013, for an excellent summary of related literature). Such considerations are outside the scope of this study.

In addition, this study only examines relationships related to creation of direct jobs, due to unavailability of data for indirect and other employment effects. Jouanjean and te Velde (2013) note that it is very important for DFIs to develop their reporting to account also for indirect jobs, induced effects and second order growth effects, as employment effects in some type of projects (e.g. infrastructure) are mostly indirect. Hence, examining only direct jobs may only paint a partial or even wrong picture of the dynamics related to overall job creation in an economy.

This study also does not test the impact of DFI funding on employment growth against any other firm financing source. Even if DFI funding might have a positive employment effect on firm-level, the effect needs to be analyzed relative to potential effects of alternative funding sources for developing country firms, as well as opportunity costs of DFI funding for the society, before making any policy decisions. For instance, Schreiner and Yaron (1999) provide an excellent framework for measuring the social cost of DFIs, which helps to answer the ultimate question of whether subsidizing DFIs is a good use of public funds or not.

1.6 Structure of the thesis

The rest of this paper is structured as follows. Section 2 presents the theoretical background and the previous empirical findings on firm-level job creation determinants and the link between DFI funding and job creation. Section 3 summarizes key insights from reviewed literature into testable hypotheses. Section 4 describes the data and the variables used in the study, as well as presents some key descriptive statistics of the data. In Section 5, econometric methodology used to test the developed hypotheses is outlined and discussed. Empirical results are presented in Section 6, first performing an analysis of the firm-level job creation determinants in DFI investments and subsequently examining the effect of DFI funding on employment growth of sample firms. Section 7 concludes the paper and gives suggestion for further research.

2. Literature review and theoretical framework

2.1 Determinants of job creation in DFI investments

2.1.1 Portfolio firm size, age and capital intensity

i. Firm size & age

There is ample literature on firm-level determinants of job creation. Within this literature field, firm size and its role as a determinant of job creation is probably the most widely researched topic. Traditional view of social scientists, ever since the classic study of Birch (1979, 1981) has been that small firms create the most jobs. More recently, Neumark et al. (2011) established similar results, while addressing methodological criticism of Birch (1979, 1981) as proposed by Davis et al. (1996). Similar results have also been found outside of U.S., with e.g. Brixy and Kohaut (1999) finding a negative relationship between firm size and employment growth in Germany. One explanation used to explain this phenomenon is that large employment share of small businesses reflects inefficient allocation of resources and lower productivity relative to large businesses.

However, a significant change to the status quo of firm size as an employment growth determinant was provided by Haltiwanger et al. (2013). Haltiwanger et al. (2013) find that actually firm age, rather than firm size acts as a driver of employment growth. Incorporating firm age into their model, they establish a strong negative relationship between firm age and employment growth and statistical insignificance of firm size. They attribute this to an "up-or-out" dynamic, where the most productive entrant companies expand and the weakest ones are driven out of business; as a result, it is the young and fast growing firms, as well as the large firms that create the most jobs. They conclude that the link between firm size and employment growth, previously so established in the field, is attributable to a strong positive correlation between firm age and size.

Criscuolo et al. (2014) find support for this "up-or-out" dynamic also outside of U.S., in other OECD countries. However, they find firm size to have a significant, negative relationship on employment growth even after controlling for firm age. They conclude that disaggregating the age profile of businesses within different size classes provides complimentary insights to an analysis based solely on size dimension.

Extrapolating naïvely these findings from developed countries into a developing country can however potentially be problematic. As Kok et al. (2013) notes, characteristics and features of SMEs in developing countries differ strongly from developed countries. Large chunk of developing country SMEs are micro sized firms with low productivity that are born out of necessity, operating in crowded market segments with low entry barriers. This is a strongly different company profile to how SMEs are typically seen in developed countries. Therefore, it is unlikely that all socioeconomic benefits associated with SMEs in developed countries also apply in the context of developing countries (Kok et al, 2013). This notion is somewhat supported by findings of Rijkers et al. (2014), who using a unique developing country dataset from Tunisia conclude that while small firms generate most jobs, this effect is both smaller than suggested by developed country literature, sensitive to measurement error and dissapears when controlling for firm age. Results of Ayyagari et al. (2016) however suggest that even when controlling for firm age, small firms have higher employment growth rates in majority of developing countries.

ii. Capital intensity

Relationship between firm capital intensity and employment growth is described by the classic Cobb-Douglas production function (Cobb and Douglas, 1928), which has been widely tested to hold in various empirical settings at firm-level. Implications of the Cobb-Douglas production function on capital intensity and employment growth relationship is that if output (Y) remains fixed and amount capital (K) is increased, amount of labor (L) must decrease. Thus, an inverse relationship between firm-level capital intensity and employment growth can be expected.

Contrary to the traditional Cobb-Doublas logic, e.g. Bigsten and Gebreeyesus (2007) find a positive link between capital intensity and employment growth in Ethiopia. They conclude that access to credit, which enterprises can use to grow their capital stock and modernize their production process, may have a positive effect on employment growth. This indicates that Cobb-Douglas relationship between firm capital intensity and employment growth does not necessarily hold in all settings and thus there is value to studying the relationship in new research contexts.

iii. DFI related literature

While there is no peer-reviewed literature on investment-level (i.e. firm-level) determinants of job creation in DFI investments, some practitioner reports exist. For instance, International Finance

Corporation (2013) analyzes data from 106 countries and over 20,000 firms, establishing a negative relationship with job creation for both firm size and age. Even though IFC (2013) findings support the idea of both *size* and *age effect* persisting in developing countries and in DFI investments within these countries, they lack the methodological rigor of most recent peer-reviewed papers on firm-level employment growth, such as Haltiwanger et al. (2013) and Rijkers et al. (2014). This calls for a need to examine the relationship between size, age, capital intensity and job creation of DFI investee firms, while addressing appropriate methodological concerns.

2.1.2 Returns on DFI portfolio firm

There exist two relevant fields of literature concerning the relationship between financial returns and employment growth in DFI investments. First one relates to studies looking explicitly at DFI investments and the relationship between returns and job creation of these investments. IFC (2007) reports in a monitoring exercise on a strong correlation between investment projects' financial performance and development outcomes, showing that 97% of projects with satisfactory or excellent financial performance led to a high development impacts. More specifically concerning job creation, only Wilton and Allen (2012) seem to have explicitly examined the relationship between return on DFI investments and the firm-level job creation of these investee firms. Analyzing data from 82 private equity funds (519 portfolio companies) in DFIs' portfolio they find a positive correlation between fund IRR and job creation, with each 1% increase in IRR being associated with a 6.3% increase in firm-level employment growth.

Regardless of the scarcity of literature on return-job creation relationship of DFI investments, there seems to exist a surprisingly widespread consensus amongst DFI professionals and other DFI literature, on a positive relationship between returns on DFI investments and the job creation impact of these investments. This is especially interesting, considering that studies which have established such a relationship, i.e. IFC (2007) and Wilton and Allen (2012), are both practitioner reports lacking the methodological scrutiny of peer-reviewed literature.

Secondly, as financial returns received by an investor from an investee firm are closely traceable to financial performance or expectations of future financial performance of the investee firm, literature on the relationship between firm-level financial performance and employment growth is relevant to this study. Several studies have examined the role of firm-level profitability as a determinant of employment growth. Studying financial factors affecting firm-level profitability and employment growth of Greek manufacturing firms, Agiomirgianakis et al. (2006) find a strongly positive relationship between company profitability metrics, such as sales profit margin and ROI, and employment growth. Broadman and Recanatini (2001) also establish a weak, but positive relationship in firm profitability and net employment growth of Russian firms during years 1996 to 1999. More recently, using a unique developing country dataset from Tunisia, Rijkers et al. (2014) find a positive, but once again weak association between net job creation and firm profitability. If assuming that firm financial performance is related to returns received by an investor from an investment into the firm, literature on firm-level financial performance and firm-level employment growth would seem to provide at least a theoretical basis for the findings of IFC (2007) and Wilton and Allen (2012).

2.2 DFI funding and job creation

Studies on relationship between DFI funding and job creation have to date focused purely on macro-level effects. Massa (2011) examines impact of DFIs on economic growth in general *via* GMM methodology on a panel dataset of 101 countries during the period 1986-2009. She finds that a 10% increase in multilateral DFIs' investment commitments may increase growth by 1.3% in lower-income and 0.9% in higher-income countries. Whilst Massa (2011) does not specifically examine the impact of DFIs on country-level job creation, considering the established relationship between aggregate output and employment, also known as Okun's Law, (Okun, 1962), inferences on likely positive employment effect can be made. Examining specifically DFIs' impact on job creation, Jouanjean and te Velde (2013) perform a thorough quantitative analysis using a dataset covering DFI activity in over 70 developing countries for the year 2007. They find that during their sample year, 2.6 million jobs created in sample countries were attributable to the activities of DFIs studies. In addition, they also present an overview of existing approaches and studies examining the job impact of DFIs and conclude that there is no literature examining effect of DFI participation on job creation at a micro (firm) level.

Jouanjean and te Velde (2013) also outline a theoretical framework on how DFIs can affect job creation on country and firm-level. They classify channels through which DFIs' actions may influence job creation as *direct* effects (*additionality* and *composition effect*) and *indirect* effects. Of these DFI action channels presented by Joujean and te Velde (2013), only *direct* effects are however meaningful in micro-level analysis. *Additionality* refers to DFIs aim to be additional to other financial flows in recipient country and solving market failures by providing finance in markets (both countries and industries), where firms face insufficient access to finance. To the extent that DFI's investments are *additional*, they will increase the overall level of economic activity, and will likely increase employment (Jouanjean and te Velde, 2013). *Composition effect* essentially refers to DFIs tendency to support firms and intra-firm activities, which are innovative and transformational. As empirical studies in both developing and developed countries have established that innovation and employment growth typically goes hand in hand (see e.g. Kannebley Jr. et al., 2010 and De Kok et al., 2011) *compositon effect* acts as a channel for DFI investments to increase firm-level employment growth.

Framework proposed by Jounjean and te Velde (2013) is highly similar to ideas of *financial benefits* of venture capital (VC) funding that VC funded firms receive. Balboa et al. (2011) summarizes rather coherently that benefits from venture capital funding to investee firms can occur either as benefits related to accessing i) *additional financial resources (financial benefits)* or ii) *value added services (non-financial benefits)* provided by the venture capitalist. Whilst there is no literature devoted directly to evaluating the impact *non-financial benefits* of DFIs, a number of empirical studies have examined *non-financial benefits* that VC funds provide to their investees.

Large and Muegge (2008) provide an excellent summary on empirical studies on *value added activities* of venture capitalists. They identify eight different categories of such *non-financial benefits* present across empirical studies, of which they conclude *operating, outreach, consulting, mentoring* and *recruiting* seem to be the most influential. *Operating* activities include VCs providing direct, hands-on managerial involvement (e.g. active planning, monitoring and controlling) to the investee firm. *Consulting* involves providing intelligence and expertise to aid senior managers and professionals of portfolio company in decision making, while *mentoring* provides more spontaneous and on-demand support often required by managers in coping in the dynamic startup environment. VC funds also provide especially valuable services in helping to establish connections and contacts with key external stakeholders (*outreach)* and in helping to locate the best talent and committing them to join *(recruiting)*. Supportive evidence on presence of such VC value added services is provided by Jääskeläinen et al. (2006) and Balboa et al. (2011), who both find that the amount of attention devoted by VC funds to their portfolio companies, as measured by the number of portfolio firms managed per investment manager, is strongly associated with portfolio company performance.

Even though studies on non-financial benefits of VC funding do not directly concern DFIs, considering that DFI activity is in many respects highly similar to VC activity, insights from VC literature seems highly relevant and applicable to DFIs. In addition, literature of more practical nature documents DFIs catering several non-financial benefits on firm-level to organizations. Comparing practices and activities of different DFIs, Kingombe et al. (2011) discuss how most DFI's typically, in co-operation with local governments and other organizations, help both funding and bringing in management consultants and technical assistance required by investee firms. Te Velde and Massa (2011) estimate that annually up to $400m worth of support on advisory services for investee firms could be channeled through DFIs. Jouanjean and te Velde (2013) discuss how DFIs are active in setting economic, social and environmental performance standards, have representatives on company boards, act as catalysts in mobilizing other private investors, direct fund managers, provide technical assistance and act as a port of knowledge through which investee companies can adopt product and process innovation. Also Settel et al. (2009) reports how rationales of DFIs' investments into developing market private equity include to be "an active investor, with an active approach to corporate governance and ESG practices".

3. Hypotheses

3.1 Determinants of job creation in DFI investments

i. Size, age and capital intensity

The literature reviewed in Section 2.1.1 indicates that there are robust empirical findings on negative relationships of *firm size* and *firm age* with firm-level employment growth from both developed and developing countries. This provides good grounds to believe that both *firm size* and *firm age* have a negative relationship with job creation in DFI investments. As discussed later on in this paper, characteristics of the sample firms indicate that DFI investments seem to be skewed more towards mid-sized, established firms when compared to average distribution of developing country firms (see Section 4.2 for more details). Nonetheless, the reviewed literature documents such wide presence of *size* and *age* effects in various research contexts that it seems likely for these effects to persist, even considering the skewed nature of the DFI investee firm sample of this study. Thus the following testable hypotheses can be formulated:

Hypothesis 1.1 ($H1.1_a$): *Firm size* is negatively related with job creation of DFI investments.

Hypothesis 1.2 ($H1.2_a$): *Firm age* is negatively related with job creation of DFI investments.

Following the Cobb-Douglas intuition (Cobb and Douglas, 1928), which has been tested widely across various empirical settings, if output (Y) for a firm remains fixed and the amount capital (K) is increased, the amount of labor (L) must decrease. Also, considering the rather limited amount of empirical studies finding support to a contrary relationship between firm-level capital intensity and employment growth (namely Bigsten and Gebreeyesus, 2007), a negative relationship between the two variables in sample firms is expected. Thus the following hypothesis can be formulated:

Hypothesis 1.3 ($H1.3_a$): *Firm capital intensity* is negatively related with job creation of DFI investments.

For each of the Hypotheses 1.1 – 1.3, there is a respective *null-hypothesis*, which is formulated as follows; *firm size* ($H1.1_0$), *firm age* ($H1.2_0$) and *firm capital intensity* ($H1.3_0$) has no statistically significant relationship with job creation of DFI investments.

ii. Financial returns

As discussed in Section 2.1.2, the DFI literature available to date on the link between portfolio firm returns and job creation in DFI investments has found a positive relationship to between the two variables. Also as discussed in Section 2.1.2, these studies have methodological issues, which this paper aims to address - Wilton and Allen (2012) for instance do not control their regression specifications for firm size or age, as specified by Haltiwanger et al. (2013) and Rijkers et al. (2014) nor for capital intensity in any form.

On the other hand, literature related to firm financial performance, such as firm profitability, and firm employment growth has predominantly concluded on a positive relationship to between the two, even when controlling for firm size and age (e.g. Broadman and Recanatini, 2001, Agiomirgianakis et al., 2006 and Rijkers et al., 2014). Considering the economic intuition that good firm financial performance should over time also yield good financial returns, findings of Broadman and Recanatini (2001), Agiomirgianakis et al. (2006) and Rijkers et al. (2014) offer convincing support to expect a positive relationship between financial returns and job creation in DFI investments studied in this paper. Thus the following testable hypothesis can be formulated:

Hypothesis 1.4 (H1.4$_a$): *Financial returns* are positively related with job creation of DFI investments.

For Hypothesis 1.4, the *null-hypothesis* is as follows; *financial returns* have no statistically significant relationship with job creation of DFI investments (H1.4$_0$).

3.2 DFI funding effect on job creation

Literature reviewed in Section 2.2, suggests two key ways in which DFI funding could impact firm-level employment growth: DFIs provide firms with i) *additional financial resources (financial benefits)* and ii) *value added services (non-financial benefits)*. Due to nature of available data, it is not possible to examine separately how *financial benefits* and *non-financial benefits* associated with DFI funding impact firm-level employment growth. However, it is possible to examine generally the effect DFI funding has on job creation at firm-level.

This effect is examined by comparing sample firms receiving additional funding (i.e. capital infusions)[1] from their "owner" investment funds (i.e. indirectly from DFI) to firms not receiving additional funding from their investment funds. As DFIs typically participate *pro-rata* in such capital infusions of their investee investment funds, rest of the paper will refer to *additional funding received by sample firm from investment fund* as *additional DFI funding* or simply *capital infusion*.

Comparing the employment effect of additional funding provided to some sample DFI investee firms against characteristically similar sample DFI investee firms not receiving additional funding, can be considered somewhat similar to examining the employment effect of DFI funding for firms receiving such funding in general *versus* firms never receiving such funding. Performing such an analysis thus allows to make causal inferences of the relationship between DFI funding and firm-level employment growth.

Literature reviewed in Section 2.2, outlines several theoretical channels through which DFI funding can impact firm-level employment growth in a beneficial way. Both through the *additionality* and *composition* effect (Jouanjean and te Velde, 2013), DFI investment dollars should be able to increase the pace of employment growth by investing into most finance-constrained and innovative firms. Also several *non-financial benefits* of DFI funding, as outlined by both relevant practitioner literature (e.g. Kingombe et al., 2011, te Velde and Massa, 2011 and Jouanjean and te Velde, 2013) and applicable research from the VC field (e.g. Jääskeläinen et al., 2006, Large and Muegge, 2008 and Balboa et al., 2011) indicate that DFI funding should have a positive effect on firm employment growth. Thus the following testable hypothesis can be formulated:

Hypothesis 2 ($H2_a$): *Additional DFI funding* has a positive effect on firm-level employment growth.

For Hypothesis 2, the *null-hypothesis* is as follows; *additional DFI funding* has no statistically significant effect on firm-level employment growth ($H2_0$).

[1] Capital infusions observed in the study can be essentially either i) executions of prior promised financing commitments or ii) entirely new financing rounds. The study will not separate between these two capital infusion categories.

4. Data and descriptive statistics

4.1 Data

This paper utilizes a unique, proprietary dataset of development finance institution investments provided by Finnfund (Finnish Fund for Industrial Cooperation Ltd), Finland's primary DFI. It consists of firm-level data from portfolio companies of investment funds into which Finnfund has invested. The original dataset includes data on 451 companies from 42 investment funds over the period of 2008 to 2014, i.e. 7 years. However, at least one annual observation on the key variable of interest, *net employment growth (%)*[2], was available for only 239 companies for the original sample – this acts as the major sample size limiting factor of the study. For these 239 companies, there is on average 3.3 annual employment growth observations, with a minimum of one annual observation and maximum of seven annual employment growth observations per company. This sums up to a total of 783 firm-year observations during the period 2008 to 2014.

Other key variables of the dataset include both *firm total investment* (i.e. the total amount in EUR invested by the Finnfund backed investment fund into a portfolio firm) and *firm fair value* for firm *i* at year *t*, as well as *year of initial investment* into firm.[3] *Firm fair value* is an objective, fair value estimate of a portfolio firm value provided by the investment fund managing the investment into firm *i* at year *t* and has been prepared in accordance to industry standards and regulations. Lastly, descriptive data on portfolio firms, such as *firm geography*, *firm sector* and *asset class*[4] was also provided.

Year of initial investment into firm is used as a proxy for *age of firm,* allowing to analyze the relationship between firm size, age and employment growth (see Section 5.2 for more details). *Firm total investment* is used for computing firm-level capital intensities and together with *firm fair value* for computing a measure of portfolio firm implied returns. This allows to examine how firm capital intensity and returns of DFI investments are related to firm-level employment growth of sample DFI investee firms (see Section 5.2 for more details).

[2] See Section 5.2 for exact definition of *net employment growth* variable used in this study.
[3] See Section 5.2 for exact definitions of *firm fair value* and *firm total investment* variables.
[4] This refers to whether the reporting investment fund has an *equity*, *debt* or *mezzanine* investments in the sample portfolio firm.

In addition, *firm total investment* is used in the second part of the paper for analyzing the effect of additional DFI funding on sample firm employment growth. This analysis is performed by examining how employment growth in year *t* is affected for sample firms whose *firm total investment* has increased from year *t -1* to year *t*. In this analysis, also *year of initial investment*, *firm sector* and data on *GDP* and *GDP growth* of sample firms' domicile country is utilized. *GDP* and *GDP growth* is obtained from World Development Indicators (WDI) databank managed by the World Bank.

All of the firm-specific variables discussed above were mostly available in the original dataset for the same firm-year observations as data on firm *net employment growth*. However, for the few firm-year instances where no observations for an explanatory variable are available to be paired with corresponding *net employment growth* observations, including such explanatory variables into a regression model further decreased the sample size of the performed analysis. This issue was predominantly related to *firm total investment* and *firm fair valuation* variables, but did not result in a dramatic decrease of sample size in any of the performed analyses.

As the study utilizes a non-exhaustive panel data set of DFI investee firms during the period 2008-2014, where not all firms have data for all variables for each year, it is meaningful to report both the number of firm observations and number of firm year observations per specific variable category. ***Figure 1***, ***Figure 2*** and ***Figure 3*** show the distribution of sample across firm geography, industry and investment asset class. Also, see ***Figure 4*** and ***Figure 5*** in **Section 5.2**, for distribution of sample firm-year observations across firm size and age of investment.

Figure 1. Distribution of firm sample across geographies

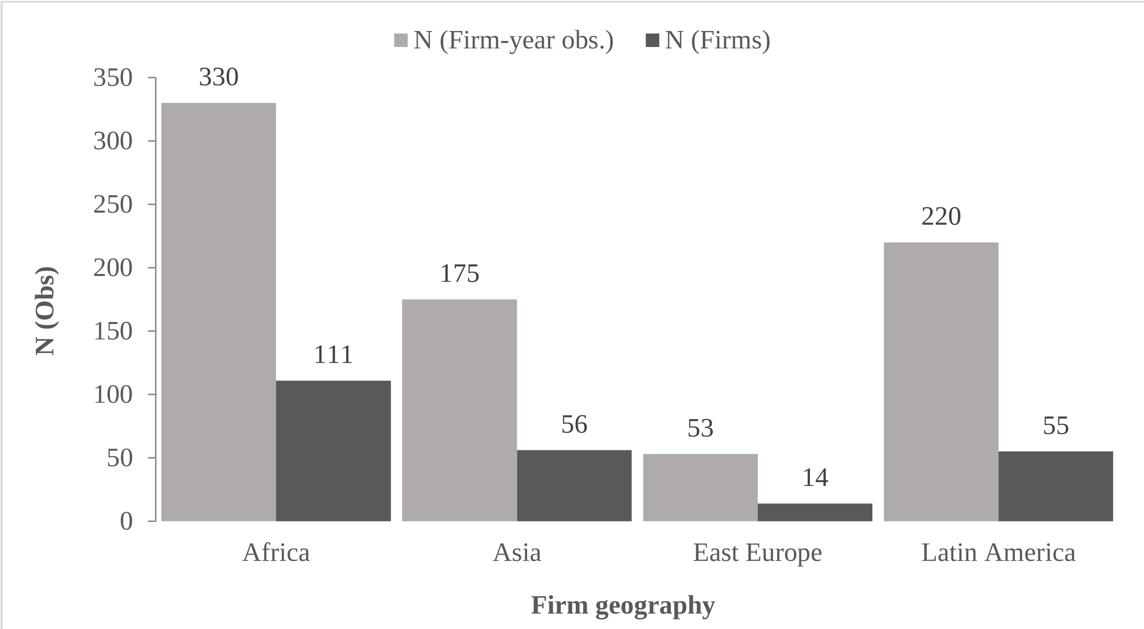


Figure 2. Distribution of firm sample across industries

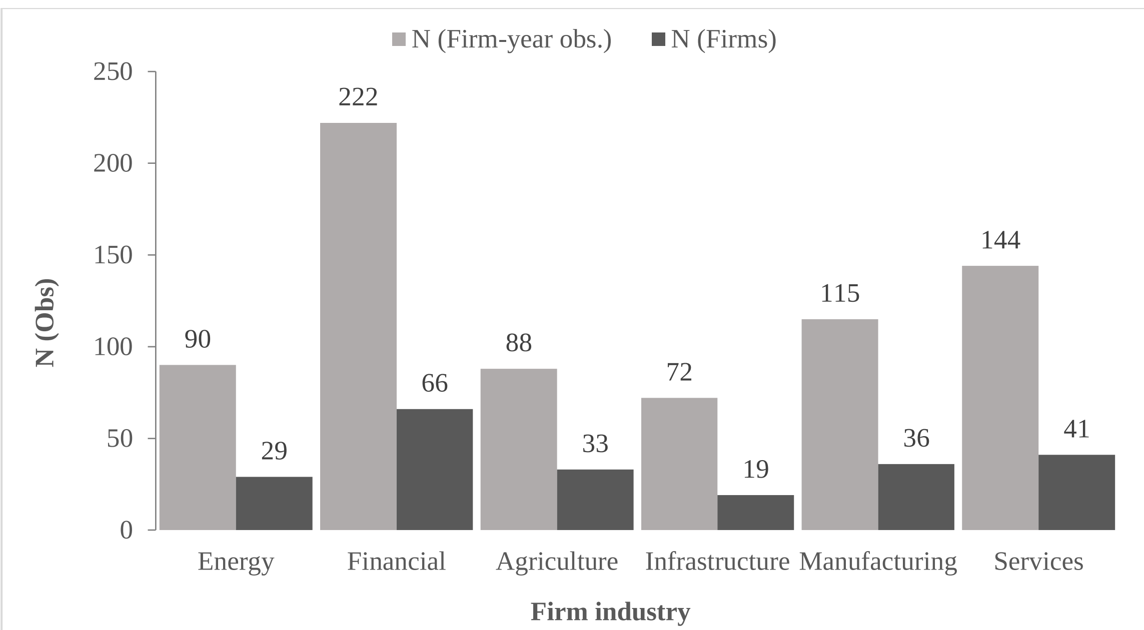
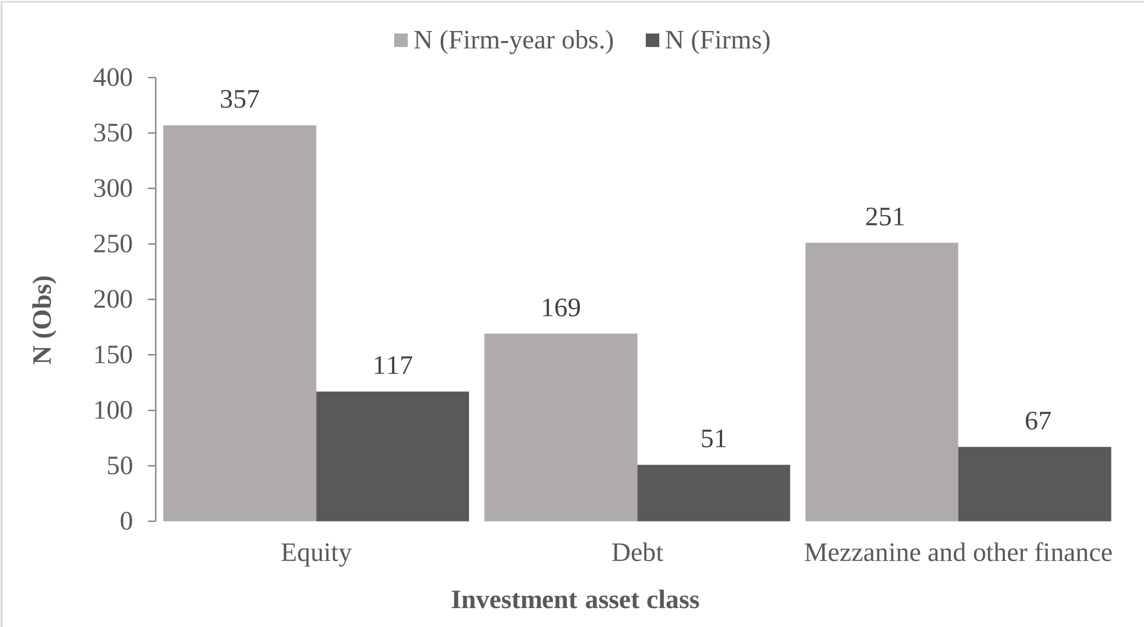


Figure 3. Distribution of firm sample across asset classes as a DFI investee firm



4.2 Descriptive statistics

Table 1 presents the summary statistics of key firm-level variables for sample firms, used in this study. The presented statistics are computed using all available observations for 239 Finnfund investee firms, included in the final sample, during the years 2008 to 2014. The exact definitions for each reported variable are specified in the notes of the table.

A summarizing look at the firm sample, as presented in Table 1 reveals several interesting insights. Firstly, mean firm size of the sample is a surprisingly high 500 employees and the median firm size is also nearly 200 employees. This implies that DFI investments are skewed more towards mid-sized and established firms, rather than small firms. This skew is also evident from ***Figure 4*** in **Section 5.2**, which shows the distribution of sample's firm-year observations across firm size categories. Figure 4 shows that firms with 50-500 employees comprise over 59% of all firm-year observations of the sample. For perspective on the firm size distribution of sample firms, Rijkers et al. (2014) find that Tunisian firm universe is heavily skewed towards small firms, with one-person firms comprising approximately 83% of all firms in their sample.

Table 1. Summary statistics

Summary statistics of the key firm-level variables from sample firms. The sample includes annual observations on these variables from 239 Finnfund investments during the years 2008 – 2014.

	All sample firms								
	N (obs)	***N (firms)***	***Mean***	***St. Dev***	***Median***	***1st qrt.***	***3rd qrt***	***Min***	***Max***
Firm size (# of emp)	783	239	500	863	195	79	521	0	7,151
Employment growth (# of emp)	783	239	40	232	8	-4	49	-2672	2,214
Net employment growth rate ($g_{i,t}$)	783	239	8.5%	39.0%	5.7%	-3.5%	21.8%	-200%	200%
Firm fair value (000' EUR)	618	228	5,029.6	9,138.5	1,602.1	529.9	5381.0	0.0	76,957.3
Firm total investment (000' EUR)	620	228	4,234.6	6,267.8	1,561.5	716.2	4,516.7	65.5	39,993.5
Firm capital intensity (000' EUR)	619	227	47.2	155.1	10.5	3.8	29.8	0.1	2,086.7
FV/IV ratio	620	228	1.09	0.68	1.00	0.75	1.28	0.0	4.76
FV/IV ratio growth (%)	469	197	1.2%	50.7%	0.0%	-20.0%	13.8%	-100%	542%
Capital infusion (% of total investment)	127	96	66.6%	159.8%	23.9%	5.9%	61.9%	0.0%	1184.3%

Firm size is equal to the number of employees in firm *i* at year *t*. *Employment growth* is the change in firm size from year *t-1* to year *t*. *Net employment growth*, $g_{i,t}$ is defined as the change in employment from year t−1 to year t, divided by average firm size: $g_{i,t} = 2\frac{E_{i,t}-E_{i,t-1}}{E_{i,t}+E_{i,t-1}}$, where $E_{i,t}$ denotes employment in firm *i* at year *t* (see Section 5.1 for more details). *Firm fair value* is an objective, fair value estimate of firm value for firm *i* at year t, provided by the investment fund that has invested into the company. *Firm total investment* is the sum of cumulative fund investments into firm *i* at year *t*. *Firm capital intensity* is defined as the ratio of *firm total investment* for firm *i* at year *t* to *firm size* for firm *i* at year *t*. FV*/IV ratio* for firm i at year t is equal to ratio of fair value of firm *i at* year *t* to *firm total investment* for firm *i* at year t (see Section 5.2 for more details). *FV/IV ratio growth* is equal to the change in *FV/IV ratio* from year *t-1* to year *t*. *Capital infusion* is equal to change in *firm total investment* for firm *i* from year *t-1* to year *t*.

Considering that the firm sample of Rijkers et al. (2014) essentially comprises the entire firm universe of Tunisia, this simple comparison quickly highlights the difference between a typical DFI investee firm and a typical firm from the general developing country firm population. Even though firm sample of Rijkers et al. (2014) only covers one specific case of firm size distribution in a developing country, similar findings have been established by Wiboonchutikula (2002) from Thailand. Wiboonchutikula (2002) shows that in Thailand, firms with less than 300 employees comprised 98.8% to 97.7% of the entire firm universe during the year 1987 to 1996. Considering that relative prevalence of small firms in countries is known to be negatively related to national income per capita (see Poschke, 2014, for an excellent overview of related literature), it seems highly likely that DFI investee firms in general do not represent a typical developing country firm with regards to firm size and possibly other firm characteristics. This highlights the importance of examining firm-level employment growth determinants (e.g. firm size, age and capital intensity) that have been established in firm samples following a firm characteristic distribution typical to developing countries (e.g. Rijkers et al., 2014), in a DFI context, which does not seem to follow such a distribution.

As indicated by Table 1, on average, sample firms have exhibited an 8.5% annual employment growth during 2008 to 2014. This figure is in line with IFC Job Creation Study (2013), where *via* enterprise surveys an average annual employment growth rate of 8.8% for DFI portfolio firms in the services sector and of 5.2% for DFI portfolio firms in the manufacturing sector over the period of 2006 to 2010 is found. It is challenging to compare the average employment growth rate of this paper's sample firms directly to other, non-DFI contexts, due to the very heterogeneous distribution of the sample across firm geographies, industries and size classes. However, even without such out-of-sample comparisons, the observed 8.5% average annual employment growth rate does suggest a healthy company expansion rate and would support the idea of sample DFI investee firms being in established growth stages.

Average employment growth rate for the sample is especially interesting in comparison with the average growth rate of firm valuation (FV/IV ratio growth %). While employment has annually grown at 8.5%, firm valuation has only increased on average by 1.2% over the period. This would again support the idea of sample firms being on average in growth phases, as when firms expand rapidly (e.g. *via* external capital financing) it seems intuitive that growth pace in number of employees for such firms would exceed the growth pace of their financial performance and thus also firm valuation.

Capital infusions, i.e. cases of additional DFI funding, are significantly present in sample firms. Nearly half of sample firms (40.1%) receive a capital infusion at some point during the years 2008 to 2014. These capital infusions are also significant in size, with average additional investment of a DFI backed investment fund being 66.6% and median 23.9% of fund total investment with firm.

As mentioned previously in Section 3.2, DFIs typically participate *pro-rata* in such capital infusions of their investee investment funds.

5. Research methodology

5.1 Dependent variable

The aim of the study is to examine which firm characteristics act as determinants of job creation in development finance investments and to investigate the effect that DFI funding has on job creation. Following the methodology used by some of the most seminal papers on job creation determinants, i.e. Davis et al. (1996) and Haltiwanger et al. (2013) and more recently Rijkers et al. (2014) in a developing country context, job creation is measured as net employment growth, $g_{i,t}$ where the change in employment from year $t-1$ to year t, divided by average firm size. More specifically, $g_{i,t}$ is define as follows: $g_{i,t} = 2\frac{E_{i,t}-E_{i,t-1}}{E_{i,t}+E_{i,t-1}}$, where $E_{i,t}$ denotes employment in firm *i* at year *t*. $g_{i,t}$ is the dependent variable in all regression specifications examining net employment growth (or also alternatively called *job creation*).

5.2 Hypothesis I

To analyze the relationship between firm size, firm age and job creation of DFI investments, following Haltiwanger et al. (2013) and Rijkers et al. (2014), net employment growth is regressed on firm size and age dummies separately and subsequently jointly. Parting from these previous studies, only base year size classification of firms is used in assigning firms to different size categories.[5] *Base year firm size* is measured as firm size in the previous year (i.e. year *t* – 1) for all firms and size classes are selected following Haltiwanger et al. (2013). ***Figure 4*** shows the distribution of sample firm-year observations across the firm size categories used in this study.

Due to unavailability of a direct firm age measure, sample firms are grouped into age categories using *age of DFI backed investment fund investment into firm* as proxy for firm age. *Age of DFI backed fund investment into firm* (referred to as *age of investment* from here on) is defined as the

[5] Average firm size classification is used in parallel to base year firm size classification by both Haltiwanger et al. (2013) and Rijkers et al. (2014). However average firm size is not an appropriate measure for firm size in this study, as firms entering or exiting the sample at year *t* are not necessarily companies that have started or seized to exist in year *t*. Rather, they are firms in which Finnfund has decided to invest in during year *t*. Because of this, the companies entering and exiting the sample of this study will be clearly larger than companies entering or exiting samples of Haltiwanger et al. (2013) and Rijkers et al. (2014), whose datasets cover the entire firm universe of USA and Tunisia respectively. Thus, applying the average firm size classification method would significantly underestimate the likely firm size of sample firms, year before entering or year after exiting the sample of this study.

difference between the *current year*, i.e. year t for firm i and the *year of first fund investment* into firm i, i.e. year $t - n$. *Age of investment* is seen as an appropriate proxy for firm age, because DFIs often invest in companies at quite early stages. Age classification is completed following Haltiwanger et al. (2013), with slight adjustment of grouping criteria, in order to better match the prevalence of firm-year observations within the sample across different age classes (see ***Figure 5*** for distribution of sample firm-year observations across age of investment categories).

Figure 4. Distribution of firm-year observations across firm size categories

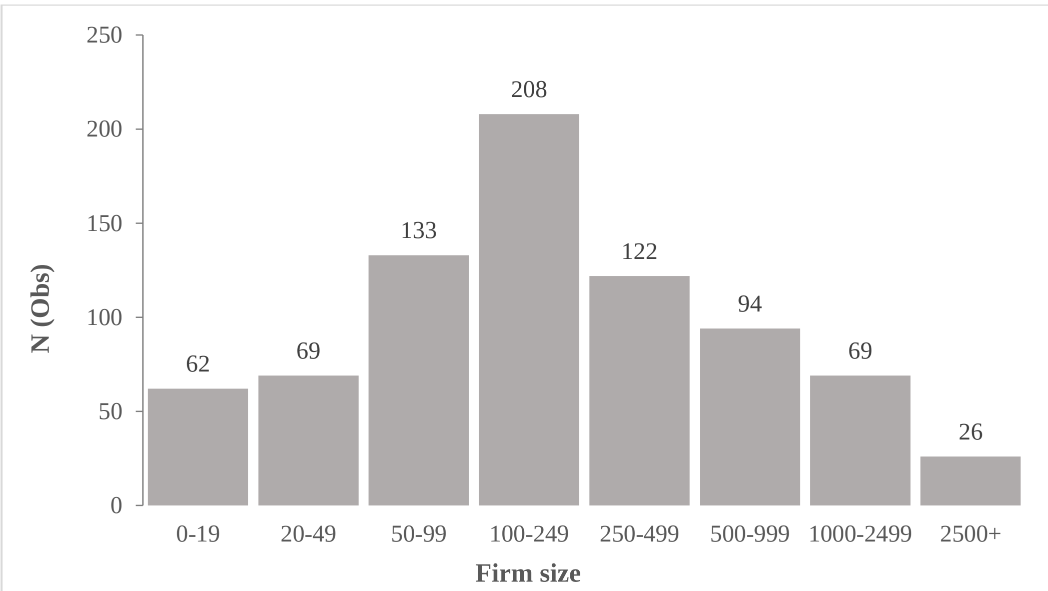
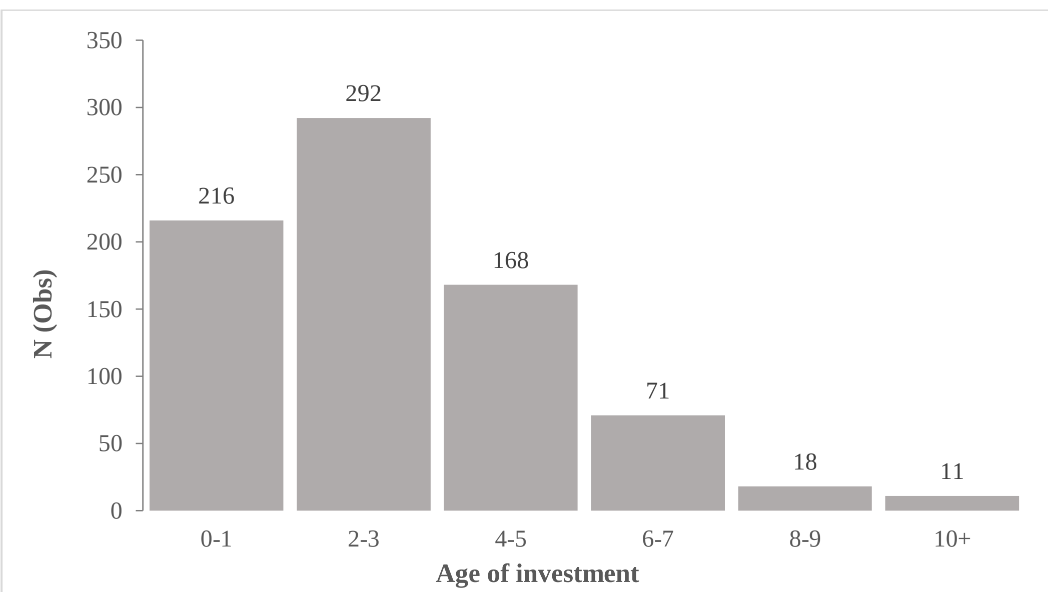


Figure 5. Distribution of firm-year observations across age of investment categories



For both size and age analysis, panel data regressions are run with company and time fixed effects, to exclude potential impacts of unobserved time and company varying factors.

Secondly, after exploring the relationship between firm size, age and job creation in the sample, methodology of Haltiwanger et al. (2013) and Rijkers et al. (2014) is extended to analyze the relationship of firm capital intensity and returns of DFI investments (i.e. implied firm returns) with sample firm employment growth. Relationship between firm capital intensity and job creation of DFI investments is examined by regressing $g_{i,t}$ on a simple measure of capital intensity, $capital\ intensity_{i,t} = \ firm\ total\ investment_{i,t}/E_{i,t}$,
where $firm\ total\ investment_{i,t}$ is the sum of cumulative DFI backed fund investments into firm *i* at year *t* and $E_{i,t}$ is the number of employees in firm *i* at year *t*. Similar to firm size and age analysis, company and time fixed effects panel data regressions are used to exclude potential impacts of unobserved time and company varying factors on the outcome variable.

Relationship between financial returns and job creation of DFI investments is examined by regressing $g_{i,t}$ on the change in *firm fair value-to-firm total investment ratio* (*FV/IV ratio*).
FV/IV ratio for firm *i* at year *t* is calculated as the ratio of *fair valuation*[6] of firm *i* at year *t* to *sum of cumulative fund investments* into firm *i* at year *t*:
$FV/IV_{i,t} = \ firm\ fair\ value_{i,t}\ /\ firm\ total\ investment_{i,t}$. Thus $\Delta FV/IV_{i,t} = \frac{FV/IV_{i,t}}{FV/IV_{i,t-1}} - 1$,
where $FV/IV_{i,t}$ denotes the *FV/IV ratio* for firm *i* at year *t* provides the implied financial return of DFI investment in firm *i* at year *t*. $\Delta FV/IV_{i,t}$ is used as a proxy for *financial return* of DFI investment into firm *i* in this paper.

Change in firm *FV/IV ratio*, rather than direct change in firm fair value is used to track financial returns from DFI investments. This is because firm *FV/IV ratio* controls for the change in firm fair value, which might be driven by the increase or decrease in *firm total investment* (occurring from e.g. additional infusions of capital by fund shareholders or ownership divestments), making it a more accurate measure of actual returns yielded by the investment.

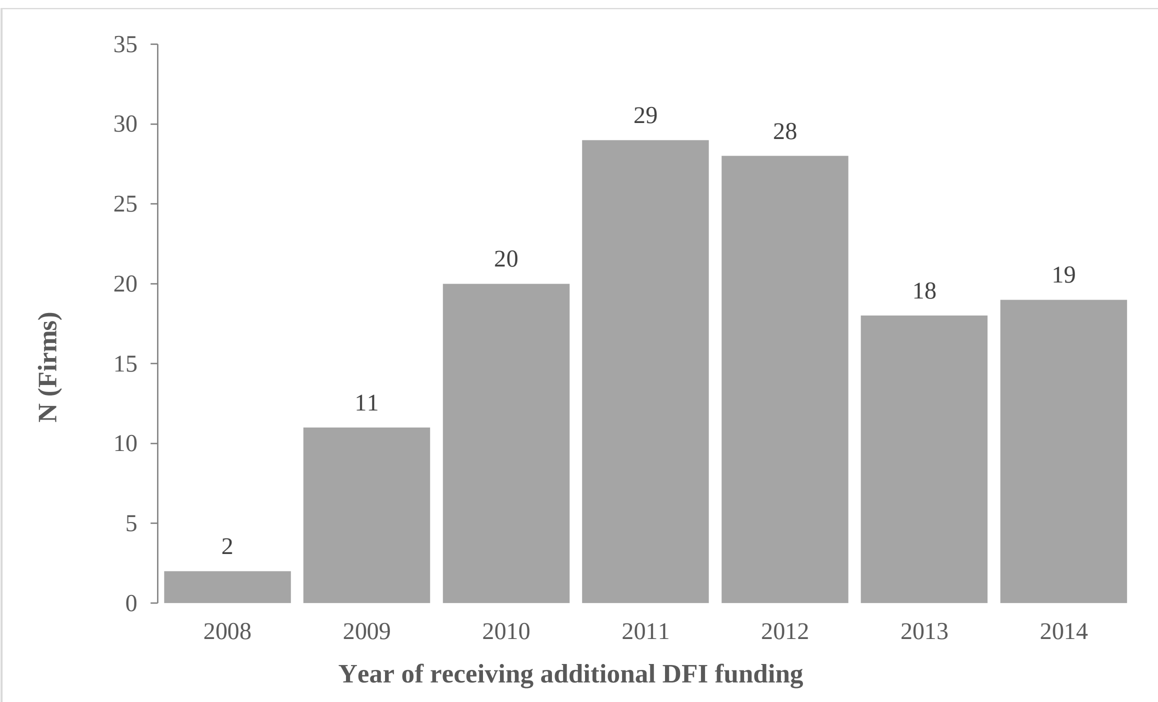
[6] *Firm fair value* is an objective, fair value estimate of a portfolio firm value provided by the investment fund managing the investment into firm *i* at year *t* and has been prepared in accordance to appropriate industry standards and regulations.

5.3 Hypothesis II

5.3.1 General methodological approach

To examine the effect of DFI funding on firm-level job creation, a series of econometric analyses is performed. Firstly, the difference between average annual employment growth of sample firms receiving additional DFI funding during year *t* and firms not receiving additional DFI funding during year *t* is compared. For this and subsequent analyses, a dummy variable for additional DFI funding, i.e. $capital\ infusion_{i,t}$ is constructed. $Capital\ infusion_{i,t}$ is assigned a value of *1* for firm *i* at year *t*, if the change in *firm total investment* for firm *i* from year *t-1* to year *t* is greater than 0 and is assigned a value of *0* otherwise. ***Figure 6*** shows the distribution of $capital\ infusion_{i,t}$ across sample years.

Figure 6. Distribution of additional DFI funding across sample years



There is however a high likelihood of an endogenous relationship existing between additional DFI funding and employment growth (e.g. portfolio firms with strong economic and employment growth *ex-ante* are probably more likely to receive additional DFI funding). Thus to establish a more robust causality relationship between the two variables, firms receiving additional funding in year *t* ("treated" firms) are matched with characteristically similar firms that did not receive additional funding in year *t* (control firms) and difference in annual employment growth between "treated" firms and matched control firms (i.e. "treatment effect" of additional DFI funding) is examined.

To perform such matching, the nearest neighbor matching (NNM) procedure (Rubin, 1973) and Kernel matching procedure (Heckman et al., 1998) are used. NNM is used as it is probably the most common and intuitive matching procedure, whilst Kernel matching is used following Imai and Azam (2012), whose study design and dataset is highly similar to those in this paper. After completing propensity score matching of sample firm-year observations with each respective matching method, difference in average annual $g_{i,t}$ between treated and control firms is compared and tested for statistical significance. Additional robustness analysis of results derived from NNM and Kernel matching methods is performed also following Imai and Azam (2012), as well as Smith and Todd (2005), *via* difference-in-difference propensity score matching (DID-PSM).

In order to complete the outlined matching procedures, estimation of propensity scores, predicting the probability of a sample firm to receive additional DFI funding during a given year, is required. The propensity scores will be estimated using two approaches; *in-sample model (ISM)* and *out-of-sample model (OSM)*. Both approaches involve estimation of logit models on the likelihood of a firm to receive a additional DFI funding during a given year, with the difference of *IS* model being estimated using all available firm-year observations, whereas *OS* model is estimated using only observations for firms prior to the period when they potentially received their first additional DFI funding.[7] In theory, latter approach should yield more robust propensity score estimates, however as discussed in Section 6.2, given the nature of the sample there are methodological issues to be considered with both approaches.

5.3.2 Selection of explanatory variables for propensity score matching

To estimate propensity scores needed in propensity score matching, logistic regressions on firm probability of receiving a capital infusion, $capital\ infusion_{i,t}$ will be run against a set of explanatory variables. Related literature and economic intuition serve as the basis for selection of explanatory variables used in propensity score estimation.

[7] For firms not receiving a single capital infusion during the entire sample, all available observations are included.

First variable to be included is *firm size*. Kingombe et al. (2011) find notable differences across DFIs according to the firm size focus of their investment practice. According to Kingombe et al. (2011), European Development Finance Institutions (EDFI) member DFIs (this includes Finnfund) are more engaged in SME finance, whereas for instance IFC DFIs tend to finance larger projects and ventures. Settel et al. (2009) also notes a skew in private equity fund focus of certain DFIs towards SME funds, rather than DFI investments being equally distributed across all firm size categories. Studying micro-level impacts of DFI financing in Ghana, Kapstein et al. (2012) find differences in firm size as one of the determinants of subsequent access to finance. More generally, Ayyagri et al. (2016) also find statistically significant differences in access to finance for different firm size classes across 50,000 firms in 70 developing countries. Thus $firm\ size_{i,t}$ is included as an explanatory variable of logistic regression, referring to the number of employees for firm *i* at year *t*.

Age of investment is second explanatory variable to be included. This is based on pure economic intuition, which goes as follows. DFI investments typically occur in several stages, either as promised total investment is being paid out in several commitments or as entirely new financing rounds occur. It thus seems intuitive that firms are more likely to receive capital infusions in early stages of their life as a fund portfolio company, rather than at later stages when they have typically established consistent cash flows and thus become financially more self-sustainable. Thus, *age of investment*, as defined previously in Section 5.2, is included as an explanatory variable.

As the third explanatory variable used in estimating the probability of sample firm to receive additional DFI funding, *firm sector* is included. Massa (2011) documents both differing degrees of DFI investment participation across different sectors and how DFI investments in different sectors yield differing impacts on economic growth of recipient country. Kingombe et al. (2011) provide a thorough comparison of practices and investment activities of key global DFIs, showing significant differences in sector focuses across DFIs. They also note that several DFIs have a *focused* strategy within specific sectors and geographies. In light of these studies, it seems likely that firm sector will have a meaningful impact of whether firm will receive additional DFI funding or not and should be included as an explanatory variable. Thus a dummy variable $firm\ sector_i$ is included as an explanatory variable and is assigned a value of *1* if firm *i* belongs to a specified sector and a value of *0* otherwise. Following typical sector classifications used in DFI literature (e.g. Massa, 2011 and Kingombe et al., 2011) sample firms are assigned as belonging to one of the following sectors: *financial*, *infrastructure*[8], *manufacturing & services* and *agribusiness.*

Lastly, both *GDP* and *GDP* growth rate are included as explanatory variables for logistic regression on $capital\ infusion_{i,t}$. Level of GDP and GDP growth rate of a country receiving foreign direct investment (FDI) are well known determinants of FDI as they are believed to be good measures of market size and market growth for investors (see e.g. Schneider and Frey, 1985, Tsai, 1994 and Bevan and Estrin, 2004). Following Schneider and Frey (1985), one year lagged measures of both GDP and GDP growth rate are incorporated into the model as explanatory firm variables used for propensity score estimation. One year lagged GDP is added to the model as *1-yr* $lagged\ log\ GDP_{j,t}$, the natural logarithm of GDP (in nominal US$) of domicile country *j* for firm *i* at year *t-1*. *1-yr* $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{\mathrm{j},t-1}}{\mathrm{GDP}_{\mathrm{j},t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of domicile country *j* for firm *i* at year *t.*

[8] Following this classification, *infrastructure* includes sample firms from both the *infrastructure* and *energy* industries of the classification used in Figure 2 in Section 4.1.

6. Empirical results

6.1. Determinants of job creation in DFI investments

6.1.1 Firm size, age and capital intensity

Table 2 presents the results of fixed-effects panel regressions of net job creation ($g_{i,t}$) on firm size and age dummies and firm capital intensity. Specifications (1) and (2) present the results of regressing $g_{i,t}$ on firm size and age dummies respectively. In specification (3) $g_{i,t}$ is regressed jointly on both firm size and age dummies. Specifications (4) reports the results of regressing $g_{i,t}$ on firm capital intensity, while specification (5) extends specification (4) by also including firm size dummies in the regression. Omitted variable for regressions including size dummies is firms with 2500 or more employees and for regressions including age dummies is firms with 15 years or more since receiving their first investment. Thus in joint regressions of firm size and age, i.e. in specification (3), the omitted category is firms with 2500 or more employees and with 15 years or more since their first investment. The coefficients resulting from specifications (1), (2), (3) and (5) are thus relative to each of these omitted categories.

Table 2. Regression results of net employment growth vs. firm size, age and capital intensity

Results of fixed-effects panel regressions of net employment growth ($g_{i,t}$) on firm size and age dummies and firm capital intensity. For all specifications, the regression is executed on all sample firms with available data and on the time period from 2008 to 2014.

	(1)	(2)	(3)	(4)	(5)
Firm size					
0-19	**1.646***** **(7.53)**		**1.532***** **(7.06)**		**1.651***** **(6.63)**
20-49	**1.069***** **(5.11)**		**0.963***** **(4.61)**		**1.041***** **(4.39)**
50-99	**0.612***** **(3.10)**		**0.507***** **(2.56)**		**0.502**** **(2.21)**
100-249	**0.464**** **(2.44)**		**0.337**** **(1.76)**		**0.385*** **(1.73)**
250-499	**0.347*** **(1.92)**		**0.254*** **(1.40)**		0.261 (1.23)
500-999	0.166 (1.01)		0.136 (0.82)		0.0063 (0.03)
1000-2499	0.113 (0.80)		0.133 (0.95)		0.143 (0.95)
Age of investment					
0-1		0.260 (0.72)	0.193 (0.59)		
2-3		0.189 (0.58)	0.151 (0.51)		
4-5		0.117 (0.40)	0.094 (0.35)		
6-7		0.150 (0.56)	0.072 (0.30)		
8-9		0.047 (0.22)	0.057 (0.30)		
Capital intensity				**-0.00075***** **(-3.10)**	**-0.00097***** **(-4.61)**
Constant	-0.505*** (-3.0)	-0.134 (-0.49)	-0.505* (-1.66)	0.0105 (0.25)	-0.419** (-2.12)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
N (obs)	783	776	776	619	619
N (firms)	239	237	237	227	227
R-squared	0.2283	0.0428	0.2302	0.0653	0.3139

All specified regression equations are computed as fixed effects panel regressions with year dummies. Dependent variable for all equations is net employment growth, $g_{i,t}$ is defined as follows: $g_{i,t} = 2\frac{E_{i,t}-E_{i,t-1}}{E_{i,t}+E_{i,t-1}}$, where $E_{i,t}$ denotes employment in firm *i* at year *t*. *Base year firm size* is used for size classification in all equations with size dummies and *age of investment* is used for age classification in all equations with age dummies. *Base year firm size* is measured as firm size in the previous year, i.e. year *t – 1*. *Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i, i.e.* year $t - n$. $Capital\ intensity_{i,t}$, is defined as $firm\ total\ investment_{i,t}\ /\ E_{i,t}$ where $firm\ total\ investment_{i,t}$ is the sum of cumulative fund investments into firm *i* at year *t* and $E_{i,t}$ denotes the number of employees in firm *i* at year *t*. Statistical significance of coefficients is denoted as follows: $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

Results of the fixed-effects panel regressions, as presented in Table 2, reveal a number of interesting relationships. First of all, in line with numerous previous studies (e.g. Davis et al., 1996, Haltiwanger et al., 2013 and Rijkers et al. 2014), a strong and statistically significant inverse relationship between firm size and employment is established. The findings imply that firms belonging to smallest firm category (0 – 19 employees) exhibited on average 165 percent higher net job creation rate than firms in the largest firm category (2500+ employees). Magnitude of the size effect is rather pronounced when comparing to findings of Rijkers et al. (2014) and Haltiwanger et al. (2013), where the corresponding employment creation premium for small firms (below 20 employees) using base size specification ranged from 1 to 20 percent and 7 to 20 percent respectively. The difference in magnitude can however, at least partially, be explained by the fact that firms in this sample, i.e. firms receiving DFI investment, are firms growing faster than a typical small firm. Also, Rijkers et al. (2014) find a rather pronounced young firm employment growth premium (ranging from 72% to 217% for firms aged 0 to 1 years), which is, as later discussed in this section, not observed in this sample. Thus it seems likely that small firms could indeed have an employment growth premium of significant magnitude, especially if they capture partially the employment growth effect of young firms.

The strong inverse relationship between firm size and job creation persists even after controlling for age of investment, i.e. the proxy for firm age in this study. Even though the behavior of *age of investment* coefficients are in line with findings of Haltiwanger et al. (2013) and Rijkers et al. (2014) both in direction and magnitude of the impact, none of the coefficients are statistically significant even at 10% confidence level.

The most likely explanation behind these results, is that even though age of investment is very likely positively correlated with firm age, this correlation is not strong enough. In other words, the proxy used for firm age in this sample is not accurate enough to produce similar results to Halitwanger et al. (2013) and Rijkers et al. (2014). Including age of investment in regression equation with size, however similarly to Haltiwanger et al. (2013) and Rijkers et al. (2014), decreases the magnitude of size effect. Controlling for age, employment growth premium for smallest firms is 153.2% and premium remains statistically significant up until 250-499 employee size category, where the premium is 25.4%.

Considering the statistical insignificance of *age of investment* in the sample, as shown in specification (2), age dummies are not included in specification (5) or in further regression analysis on the relationship between returns of DFI investments and job creation. This decision is also made due to minimal increase of model fit observed between specifications (1) and (3), with R-squared values of 0.2283 and 0.2302 respectively.

Results of regression of net employment growth on firm capital intensity, as shown in specifications (4), are statistically significant at 1% level and are in line with the Cobb-Douglas intuition. Every 10,000 EUR increase in firm capital intensity, which implies a c. 21% increase relative to the average capital intensity of sample firms[9], is associated with a 0.75% decrease in employment growth of sample firms. Interestingly, when controlling for firm size in specification (5), not only the statistical significance of the capital intensity persists at 1% but also the magnitude of the effect increases. Controlling for firm size, a 10,000 EUR increase is associated with nearly 1% decrease in firm employment growth, while one standard deviation increase in capital intensity is associated with slightly above 15% decrease in sample firm job creation – these are economically meaningful magnitudes. Inclusion of for firm capital intensity alongside firm size dummies also significantly increases the explanatory power of the regression model, as indicated by the increase of R-squared from 0.2283 in specification (1) to 0.3139 in specification (5). Thus, it seems justified to control for both firm size and firm capital intensity when subsequently analyzing the relationship between returns of DFI investments and firm-level employment growth of these portfolio firms.

All in all, based on the analysis of this section, null hypotheses $\mathbf{H1.1_0}$ and $\mathbf{H1.3_0}$ can be rejected and hypotheses $\mathbf{H1.1_a}$ and $\mathbf{H1.3_a}$ can be accepted. On the other hand, considering the statistical insignificance of *age of investment* in specifications (2) and (3), null hypothesis $\mathbf{H1.2_0}$ is accepted and hypothesis $\mathbf{H1.2_a}$ is rejected.

[9] Capital intensity for sample firms has a mean of 47,200 EUR and standard deviation of 155,100 EUR.

6.1.2 Returns on DFI portfolio firm

Table 3 presents the results of regressions of net job creation on change in portfolio firm implied returns, i.e. change in firm fair value-to-invested amount ratio (FV/IV ratio growth). In addition to basic specification (6), relationship between net job creation and change in firm implied returns is controlled for effect of firm size (7), capital intensity (8) and both firm size and capital intensity (9) respectively.

As can be seen from Table 3, returns of DFI investments have statistically significant relationship with employment growth in specification (6), where neither effect of firm size nor of firm capital intensity is accounted for, and when controlling only for capital intensity (8). When controlling for firm size, as in specifications (7) and (9), returns of DFI investments show no explanatory power in portfolio firm employment growth even at a 10% confidence interval.

In specification (6), FV/IV ratio growth is statistically significant at 5% confidence interval and can be interpreted as follows; a 10% increase in firm FV/IV ratio is associated with 0.8% higher annual employment growth of the firm. After controlling for capital intensity (8), coefficient of FV/IV ratio growth is statistically significant only at 10% confidence level and the magnitude of the effect also decreases; a 10% increase in firm FV/IV ratio is associated with 0.6% increase in employment growth. Considering that FV/IV ratio growth for sample firms is on average 1.2% with a standard deviation of 50.7%, even an increase in FV/IV ratio growth of one standard deviation would only be associated with a 3.3% increase[10] in employment growth. In other words, even if the relationship between the returns of DFI portfolio firms and their employment growth is statistically significant in some specifications, the relationship is not very meaningful economically.

[10] 0.0641 x 0.507 = 0.0325

Table 3. Regression results of net employment growth vs. DFI investment returns

Results of fixed-effects panel regressions of net employment growth ($g_{i,t}$) on DFI investment returns ($\Delta FV/IV_{i,t}$), controlling for firm size and firm capital intensity. For all specifications, the regression is executed on all sample firms with available data and on the time period from 2008 to 2014.

	(6)	(7)	(8)	(9)
FV/IV ratio growth (%)	**0.0786**** **(2.06)**	0.0473 (1.47)	**0.0641*** **(1.77)**	0.0351 (1.16)
Capital intensity			**-0.0017***** **(-5.50)**	**-0.0015***** **(-6.12)**
Firm size				
0-19		**1.446***** **(4.28)**		**1.409***** **(4.45)**
20-49		**0.5822*** **(1.81)**		**0.547*** **(1.82)**
50-99		-0.0037 (-0.01)		-0.0002 (-0.00)
100-249		-0.1329 (-0.43)		-0.141 (-0.49)
250-499		-0.2744 (-0.92)		-0.275 (-0.98)
500-999		-0.390 (-1.36)		-0.390 (-1.45)
1000-2499		0.0444 (0.20)		0.0333 (0.16)
Constant	-0.0355 (-0.75)	-0.0546 (-0.20)	0.0261 (0.57)	0.0093 (0.04)
Firm fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N (obs)	469	469	468	468
N (firms)	197	197	196	196
R-squared	0.0516	0.3588	0.1492	0.4404

All specified regression equations are computed as fixed effects panel regressions with year dummies. Dependent variable for all equations is net employment growth, $g_{i,t}$ and *base year firm size* is used for size classification in all equations with size dummies. *Base year firm size* is measured as firm size in the previous year, i.e. year *t – 1*. $Capital\ intensity_{i,t}$, is defined as $firm\ total\ investment_{i,t}\ /\ E_{i,t}$ where $firm\ total\ investment_{i,t}$ is the sum of cumulative fund investments into firm *i* at year *t* and $E_{i,t}$ denotes the number of employees in firm *i* at year *t*. FV/IV ratio growth, i.e. $\Delta FV/IV_{i,t}$ is defined as follows: $\Delta FV/IV_{i,t} = \frac{FV/IV_{i,t}}{FV/IV_{i,t-1}} - 1$, *where* $FV/IV_{i,t}$ is *FV/IV ratio* for firm *i* at year *t. FV/IV ratio* for firm *i* at year *t* is calculated as the ratio of fair valuation of firm *i* at year *t* to sum of cumulative fund investments into firm *i* at year *t. Firm fair value* is an objective, fair value estimate of company value provided by the investment fund that has invested into the company and has been prepared in accordance to industry standards and regulations. Statistical significance of coefficients is denoted as follows: $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

More generally, considering the results from Section 6.1.1, and the statistical relationships established between firm size, capital intensity and job creation in previous empirical literature (as reviewed in Section 2.1) it seems highly likely that specification (9) provides the best empirical test on the explanatory power of DFI portfolio firm returns on portfolio firm employment growth. This intuition is also supported by the R-squared statistic of 0.4404 for specification (9), which is the highest model fit for any of the specifications explaining job creation determinants examined in this paper. Based on these considerations, it can be concluded that there is no statistically significant relationship between DFI portfolio firm returns and DFI portfolio firm job creation in sample firms. Thus, null hypothesis **$H1.4_0$** is accepted and hypothesis **$H1.4_a$** is rejected.

Such conclusion highlights the potential methodological limitations of previous DFI literature, which has established a positive relationship between DFI investment returns and investment-level job creation (Wilton and Allen, 2012). This is because the analysis performed in this section follows strictly the methodology of Haltiwanger et al. (2013) and Rijkers et al. (2014), who provide some of the most recent methodological insight into studying firm-level employment growth determinants. Thus, this seems to provide strong grounds for questioning the findings of Wilton and Allen (2012). It is however worth noting, that as the results presented in this section are observed from financial returns of sample DFI investments and not from firm-level profitability directly, no explicit conclusions on the potential relationship between firm-level profitability and firm-level employment growth in DFI investments can be made.

6.2 DFI capital infusion and job creation

6.2.1 Propensity score estimation

As discussed in Section 5.3, in order to establish a potentially causal relationship between additional DFI funding and firm-level employment growth in sample firms, propensity score matching (PSM) is used to compare the difference in average employment growth between firms receiving additional funding in year *t* and firms that are characteristically similar, but did not receive additional funding in year *t*. In order to perform the PSM, the probability of each sample firm (i.e. propensity score) to receive additional DFI funding during a given year needs to be estimated. In this paper, propensity scores are estimated through a logistic regression of a dummy variable, $capital\ infusion_{i,t}$[11], which indicates whether a sample firm received additional DFI funding during a given year, on a set of observable firm characteristics that explain the difference in likelihood of receiving additional DFI funding between firms. These firm characteristics are *firm size, age of investment*, *firm sector, 1 year lagged* log *GDP* and *1 year lagged GDP growth*. Subsequently, the PSM completed using the estimated propensity scores ensures that average employment growth is compared between firms that are characteristically most similar, apart from the fact of receiving or not receiving additional DFI funding during a given year.

Table 4 shows the result of a logit regression of $capital\ infusion_{i,t}$, against *firm size, age of investment*, *firm sector,* 1 year lagged log *GDP* and 1 year lagged *GDP growth*. Coefficients reported for all explanatory variables are in terms of log odds. Specification (1) presents regression results using the *in-sample model* (*ISM*) and specifications (2) and (3) present results for the *out-of-sample model* (*OSM*). As discussed previously in Section 5.3, the propensity scores are estimated using two approaches; *in-sample model (ISM)* and *out-of-sample model (OSM)*. Both approaches involve estimation of logit models on the likelihood of a firm to receive a capital infusion during a given year, with the following difference: *IS* model is estimated using all available firm-year observations from the entire firm sample, whereas *OS* model is estimated using only firm-year observations before the year of first funding for additionally funded firms and using all available firm-year observations for firms not receiving additional funding. In theory, OSM approach should produce a more robust propensity score estimate, as each estimate is built based purely on firm characteristics observable *ex-ante* to any sample firm receiving additional DFI funding. Such an approach is more robust, as it eliminates the possibility of some potential systematic changes in the specified firm characteristics, which might occur after a sample firm receives additional DFI funding, affecting the estimated *ex-ante* probability of receiving additional funding.

As can be noticed from specification (2), only firm size and *financial* sector dummy have explanatory significance in probability of firm receiving additional funding when estimating using the *OSM* approach. Thus, specification (3) is constructed to perform an *out-of-sample* regression only on variables statistically significant in specification (2) and to be used in further propensity score estimation. Also for *firm sector,* regression equations with sector dummies for each sector

[11] See Section 5.3 for exact definition of $capital\ infusion_{i,t}$.

were estimated separately. These are reported in ***Table A-1*** and ***Table A-2*** in **Appendix 1**. Results presented in the Table A-1 and Table A-2 show that only *financial* sector has explanatory significance for both the ISM and the OSM approach. Thus, regression specifications reported in Table 4 only include *financial* sector dummy and all other sector dummies are dropped.[12]

Table 4. Logit regression results on additional DFI funding

Results of logit regression of $capital\ infusion_{i,t}$ on firm size, age of investment, 1 year lagged log *GDP*, 1 year lagged *GDP* growth and financial sector dummy. Reported coefficients are in terms of log odds. For specification (1), the regression is executed on all sample firms with available data and on the time period from 2008 to 2014. For specification (2) and (3) the regression is executed for firms receiving a capital infusion using only observations from years prior to the year when they received their first capital infusion and for firms not receiving a capital infusion using observations from all sample years.

	In-sample model	Out-of-sample model	
	(1)	**(2)**	**(3)**
Firm size	**-0.00074****	**-0.00082****	**-0.00086****
	(-2.45)	**(-1.96)**	**(-2.04)**
Age of investment	**-0.503*****	-0.117	
	(-5.58)	(-1.15)	
1-yr lag log GDP	**0.438*****	0.0014	
	(2.94)	(0.01)	
1-yr lag GDP *g*	**8.015***	-3.974	
	(1.72)	(-0.56)	
<u>*Firm Sector*</u>			
Financial	**-0.697***	**-1.062***	**-1.173****
	(-1.91)	**(-1.86)**	**(-2.11)**
Constant	-3.224**	-0.540	-1.083***
	(-2.46)	(-0.25)	(-4.54)
N (obs)	448	227	235
LR chi-squared	70.06***	14.38**	13.35***
Pseudo R-squared	0.1362	0.0712	0.0652

All specified regression equations are computed as logit regressions. Dependent variable for all specifications is a dummy variable $capital\ infusion_{i,t}$, where $capital\ infusion_{i,t}$ is assigned a value of *1* for firm *i* at year *t*, if change in *firm total investment* for firm *i* from year *t-1* to year *t* is greater than 0 and is assigned a value of *0* otherwise. $Firm\ size_{i,t}$ is defined as the number of employees for firm *i* at year *t*. *Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i, i.e.* year *t – n. 1-yr* $lagged\ log\ GDP_{j,t}$ is the natural logarithm of GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t-1*.

[12] Sector dummy variables, which are not statistically significant in both models are dropped for the purpose of maintaining comparability between different specifications, for the sake of model simplicity and to make results reported in *Table 4* as comprehendible as possible.

1-yr $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{\mathrm{j},t-1}}{\mathrm{GDP}_{\mathrm{j},t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of firm domicile country j for firm *i* at year *t*. $Financial_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the financial sector and *0* otherwise. LR chi-squared refers to likelihood-ratio (LR) chi-square test statistic, which is a test on joint statistical significance of regression coefficients. Pseudo R-squared refers to McFadden pseudo R-squared. Statistical significance of coefficients is denoted as follows: *P < 0.1; **P < 0.05; ***P < 0.01.

Results of performed logit regression yield several interesting insights. Firstly, as indicated by the likelihood-ratio (LR) chi-squared test statistic, for all specifications joint significance of regression coefficients is statistically different from zero. This means that all specifications can explain probability of sample firm receiving additional DFI funding better than a null model. *Firm size* has a statistically significant and negative relationship with probability of receiving additional DFI funding for all specifications. The coefficient for *firm size* is statistically significant at 5% confidence level for all specifications and implies that one standard deviation increase in sample firm size as measured in employees, decreases the odds of receiving additional DFI funding by about 1.89 to 2.10 times, depending on the used specification.[13] This seems to indicate that during the sample years Finnfund's support was skewed more towards SMEs, baring resemblance to general investment practices of several other DFIs (see Kingombe et al. 2011). *Age of investment* also has a negative relationship with the probability of receiving additional DFI funding in the *IS* model, but loses its explanatory power in the *OS* model. In the *ISM* specification, for every additional year passed from the DFI initial investment, sample firm is 1.65 times less likely[14] to receive additional DFI funding. This is in-line with the intuition outlined in Section 5.3.

1-yr lagged log GDP and *1-yr lagged GDP growth* are both positively associated with the likelihood of firm receiving additional DFI funding in the *IS* model. This is an expected result considering the widely recognized link between GDP and GDP growth and FDI in economic literature (e.g. Schneider and Frey, 1985 and Tsai, 1994). For one unit increase in $log\ GDP_{j,t}$ in year *t-1* for firm *i* domiciled in country *j* the likelihood of firm *i* receiving additional DFI funding increases by about 1.55 times[15]. Similarly, 1% increase in *GDP growth* increases the likelihood of

[13] Standard deviation of *firm size* is 863 employees. Converting *firm size* coefficient for (1) from log odds to odds ratio: $e^{-0.00074\ x\ 863}$ = 0.528 more likely to receive additional funding. This is equal to 0.528 / 1 = 1.89 less likely to receive additional funding. Similary, for specification (2): : $e^{-0.00082\ x\ 863}$ = 0.493 / 1 = 2.03 and for specification (3): $e^{-0.00086\ x\ 863}$ = 0.476 / 1 = 2.1

[14] $e^{-0.503}$= 0.605 / 1 = 1.654

[15] $e^{0.438}$= 1.550

receiving additional DFI funding by about 1.08 times[16]. However, as shown by specification (2), both level and growth of GDP lose their predictive power of additional DFI funding when using the OSM approach. Thus, both *1-yr lagged log GDP* and *1-yr lagged GDP growth* are dropped from specification (3), which is the OSM specification used in eventual propensity score estimation. Lastly, belonging to *financial* sector decreases the probability of sample firm to receive additional DFI funding by about 2.01 times[17] in the *IS* model and by about 3.23 times[18] in the *OS* model. In addition to *firm size*, *financial* sector dummy is the only other variable to have a statistically significant coefficient in both *ISM* and *OSM* specifications. As there was no other expectation on the relationship between *firm sector* and the probability of sample firm to receive additional DFI funding, apart from there being a difference across sectors, the estimated coefficient seems to make economic sense.

All in all, logit regressions presented in Table 4 seem to yield results that are meaningful and in-line with general economic intuition. This suggests that the presented specifications are well-suited for estimating propensity scores for sample firms. ***Table 5*** shows summary statistics for the propensity scores estimated using both the ISM and the OSM approach. ISM propensity scores are estimated using specification (1) and OSM propensity scores using specification (3), as mentioned earlier. The estimated propensity scores are used for subsequent propensity score matching and treatment effects analysis, as reported in Section 6.2.2. ***Figure 7*** shows the cumulative distribution of estimated propensity scores for both estimation approaches.

Both in Table 5 and in Figure 7, *treated* group refers to firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014 and *control* group refers to firm-year observations of sample firms that did not received additional DFI funding during 2008 to 2014. Reported propensity scores can be interpreted as the probability of a sample firm to receive additional DFI funding during the sample year, based on observed values for specified firm characteristics. These specified firm characteristics are *firm size*, *age of investment*, *firm sector (financial)*, 1 year lagged log *GDP* and 1 year lagged *GDP growth* for the ISM approach and *firm size* and *firm sector (financial)* for the OSM approach.

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[16] $e^{\frac{8.015}{100}} = 1.083$
[17] $e^{-0.697} = 2.008$
[18] $e^{-1.173} = 3.232$

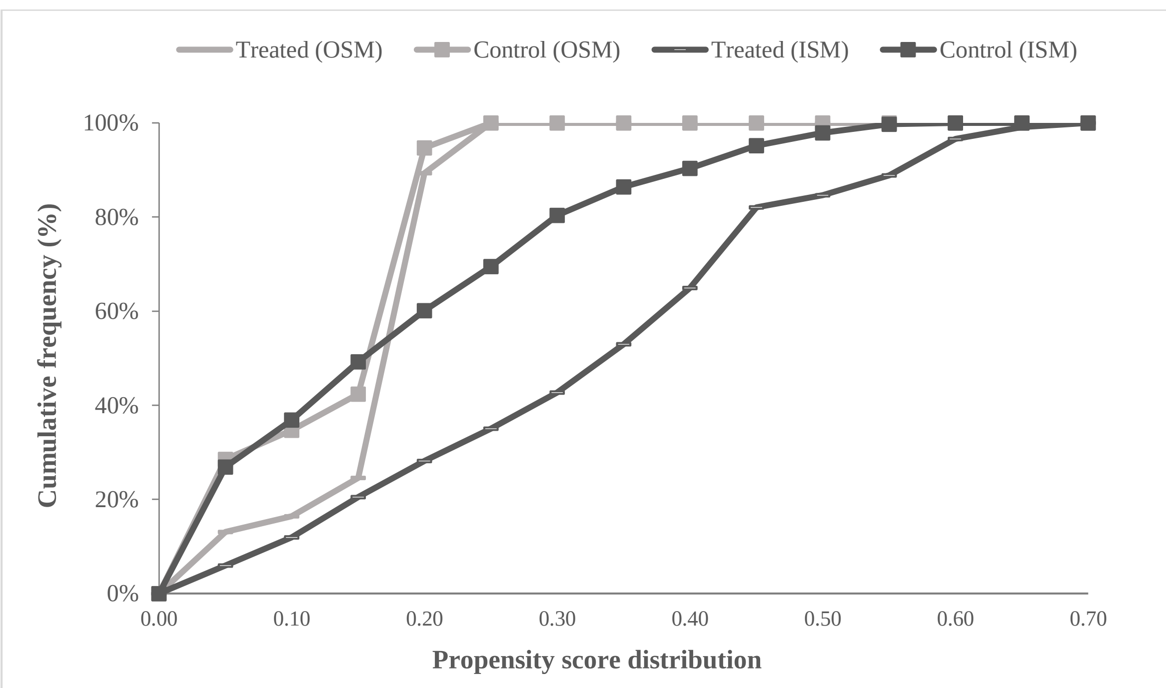
Table 5. Summary statistics of estimated propensity scores

Summary statistics of propensity scores estimated using both *out-of-sample* and *in-sample* estimation approaches. *Treated* group reports propensity scores for firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014. *Control* group reports propensity scores for firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014.

	In-sample model					Out-of-sample model				
	N (obs)	***Mean***	***Median***	***Min***	***Max***	***N (obs)***	***Mean***	***Median***	***Min***	***Max***
Propensity score (treated)	117	0.37	0.38	0.05	0.74	122	0.21	0.23	0.02	0.25
Propensity score (control)	331	0.22	0.21	0.00	0.62	340	0.17	0.21	0.00	0.25

Figure 7. Cumulative distribution of estimated propensity scores for by firm category and estimation approach

Estimated propensity scores shown for *treated* and *control* firms for both ISM and OSM estimation approach. *Treated* group reports propensity scores for firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014. *Control* group reports propensity scores for firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014.



As discussed earlier in Section 6.2.1, the OSM approach should in theory estimate more robust propensity scores for the *ex-ante* probability of receiving a capital infusion than the ISM approach. However, both the cumulative distribution of propensity scores for sample firms, as well as summary statistics indicate that the OSM approach produces significantly lower propensity scores compared to estimates produced with the ISM approach. This is evident when examining average estimated propensity scores for sample firms produced by the two approaches, which are 0.16 higher for the treated group and 0.05 higher for the control group when estimated using the ISM approach. Also with the ISM approach, over 40% of sample propensity scores are above 0.2 for the control group and above 0.4 for the treated group, while for the OSM approach less than 10% of sample propensity scores are above 0.2 for both groups. This means that specification (1) does a better job than specification (3) at explaining and quantifying the difference in probability of sample firm to receive additional funding, based on observable sample firm characteristics. Thus, propensity scores estimated using both specification (1) and (3) are used in propensity score matching performed in the next section, to provide a methodologically most holistic approach to examine the *treatment effect*[19] of additional DFI funding present in the sample.

6.2.2 Treatment effects analysis

Table 6 shows results of treatment effects analysis on net employment growth (%) during year *t* for firms receiving additional DFI funding during year *t* (i.e. treated group) and for firms not receiving additional DFI funding during year *t* (i.e. control group), for all sample periods *t*. First row of the table reports differences in the average net employment growth ($g_{i,t}$) for the treated and control firm-year observations, without employing any matching procedures. Rest of the table reports differences in average $g_{i,t}$ for the treated and control firm-year observations, where control firm-year observations are selected using the i) nearest neighbor matching (NNM) and ii) Kernel matching algorithm. NNM is performed in its simplest form, as one-to-one matching[20], where a treated firm-year observation is assigned a matching control firm-year observation based on the

[19] *Treatment effect* refers to the difference in annual employment growth between *treated* firms (i.e. firms receiving additional DFI funding in yeat *t*) and matched *control* firms (i.e. characteristically similar firms that did not receive additional DFI funding in year *t*). In other words, "treatment effects" refers to the effect additional DFI funding has on sample firm employment growth.

[20] Also known as k nearest neighbor (KNN) matching, with k = 1.

nearest propensity score (following Rubin, 1973). Kernel matching is performed following specifications Imai and Azam (2012), with a bandwidth of 0.05. In the Kernel matching algorithm, each treated firm-year observation is compared against a weighted average of multiple control firm-year observations, where assigned weights are defined by the distance of propensity scores between the given control observation and the treated observation.[21] As mentioned in previous section, both an ISM and an OSM approach is used to estimate two separate sets of propensity scores for sample firm-year observations. Thus, propensity score matching and subsequent examination of differences in average $g_{i,t}$ between the treated and control firm-year observations are reported separately for ISM and OSM, as they result in different treated and control groups.

Table 6. Treatment effects analysis of additional DFI funding

Analysis of average treatment effect (ATT) of additional DFI funding ($capital\ infusion_{i,t}$) on net employment growth ($g_{i,t}$). Results reported for unmatched, nearest neighbor matched (NNM) and Kernel matched sample firm-year observations. For all groups, average treatment effects calculated using observations from all sample firms with available data and for the time period of 2008 to 2014.

	Mean $g_{i,t}$				*N(obs)*	
Matching algorithm	**Treated**	**Control**	**ATT**	**T-stat**	**Treated**	**Control**
Unmatched	0.1357	0.0471	**0.0886****	2.13	127	355
NNM (ISM)	0.1456	-0.0233	**0.1689****	2.12	102	315
NNM (OSM)	0.1319	0.0527	0.0792	1.21	115	324
Kernel (ISM)	0.1456	0.0445	**0.1011***	1.70	102	315
Kernel (OSM)	0.1319	0.0466	**0.0853***	1.65	115	324

Matching algorithm refers to the propensity score matching algorithm used for selection of *treated* and *control* group firm-year observations. *Treated* group reports average $g_{i,t}$ for firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014 and qualified for matching against a control group using the specified *matching algorithm*. *Control* group reports average $g_{i,t}$ for firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014 and are matched to *treated* group using the specified *matching algorithm*. *ATT* reports the difference in average $g_{i,t}$ between *treated* and *control* group, where firm-year observations are selected into both groups using the specified matching algorithm. *T-stat* reports the t-statistic of *ATT*. Statistical significance of coefficients is denoted as follows: *P < 0.1; **P < 0.05; ***P < 0.01

Comparing average net employment growth for unmatched *treated* and *control* observations

[21] See Heckman et al. (1998) for technical details on Kernel matching algorithm.

indicates a statistically significant difference between the two groups. Average annual net employment growth for sample firms receiving additional DFI funding seems to be 8.9% higher than for firms not receiving additional DFI funding. However, as discussed in Section 5.3, such a naïve analysis is problematic due to potential endogeneity issues. For instance, portfolio firms with strong economic and employment growth *ex-ante* are probably more likely to receive additional DFI funding in the first place. Thus no meaningful inferences can be drawn from simply examining the difference in average net employment growth between the treated and control group.

Comparing group differences using the nearest neighbor and Kernel matching procedures resolves endogeneity issues and provides a more robust analysis of effect of additional DFI funding on average $g_{i,t}$, as it accounts for firm characteristics that increase the likelihood of receiving additional DFI funding by comparing treated firm-year observations with characteristically most similar non-treated (control) firm-year observations. To ensure the quality of matching for both matching algorithms, the balancing property of the explanatory variables used in propensity score estimation, is tested for each matching algorithm reported in Table 6. Essentially, this is a test on whether matched firm-year observations in the treatment and control groups are statistically comparable, as it examines whether explanatory variables used to predict propensity scores for each firm-year observation are similar for both groups. In practice, the balancing test is performed by computing mean values of each explanatory variable used in propensity score estimation (see Section 6.2.1 for details on explanatory variables used in estimating propensity scores) and comparing the differences in these mean values between treated and control groups, where firm-year observations are selected into treated and control groups using the specified matching algorithm.

Table 7 reports results of the balancing test for each propensity score matching algorithm used in the treatment effects analysis. As can be seen from the table, none of the used matching algorithms exhibit a statistically significant difference in mean values of observable firm characteristics between the treated and matched control group observations. This indicates that the treated and control groups are similar enough in all of the matching cases in order to make meaningful comparisons between average $g_{i,t}$ of treated and control groups.

Table 7. Balancing test on explanatory variables used in NN and Kernel matching

Balancing test on explanatory variables used estimation of propensity scores and subsequent propensity score matching using nearest neighbor and Kernel *matching algorithms*. *Treated* group includes firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014 and qualified for matching against a control group using the specified *matching algorithm*. *Control* includes firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014 and are matched to *treated* group using the specified *matching algorithm*.

	Mean		
	Treated	**Control**	**T-stat**
NNM (ISM)			
Firm size	231.53	275.26	-0.73
Age of investment	2.21	2.11	0.57
1-yr lag GDP	7.90	7.98	-0.61
1-yr lag GDP g	4.92%	4.56%	0.89
Firm sector (financial)	0.07	0.10	-0.76
NNM (OSM)			
Firm size	239.78	264.78	-0.49
Firm sector (financial)	0.08	0.06	0.52
Kernel (ISM)			
Firm size	231.53	243.71	-0.25
Age of investment	2.21	2.22	-0.10
1-yr lag GDP	7.90	7.94	-0.30
1-yr lag GDP g	4.92%	4.97%	-0.11
Firm sector (financial)	0.07	0.10	-0.72
Kernel (OSM)			
Firm size	239.78	257.14	-0.33
Firm sector (financial)	0.08	0.08	0.06

$Firm\ size_{i,t}$ is defined as the number of employees for firm i at year *t*. *Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i*, *i.e.* year *t – n*. *1-yr* $lagged\ log\ GDP_{j,t}$ is the natural logarithm of GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t-1*. *1-yr* $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{\mathrm{j},t-1}}{\mathrm{GDP}_{\mathrm{j},t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of firm domicile country j for firm *i* at year *t*. $Financial_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the financial sector and *0* otherwise. Statistical significance of coefficients is denoted as follows: *P < 0.1; **P < 0.05; ***P < 0.01.

Treatment effects analysis with both NNM and Kernel procedures, as reported in Table 6, yields exiting results. Firstly, NNM using ISM estimated propensity scores shows a statistically significant and positive effect of additional DFI funding on sample firm employment growth. On average, receiving additional DFI funding during year *t* increased net employment growth for firm *i* during year *t* by 16.9%. In other words, DFI investee firms receiving additional DFI funding experience a 16.9% boost in same year employment growth compared to DFI investee firms of very similar size, sector, time since inclusion in DFI portfolio and domicile country macroeconomic conditions, but who do not receive such funding. When propensity scores for NNM are estimated using the OSM approach, the employment effect of additional DFI funding is 7.9%, but statistically insignificant even at 10% confidence level. Interestingly, the difference in average annual employment growth between treated and control groups (ATT) is greater in the case of NNM ISM matching than in the unmatched case. This would imply that rather than the likelihood of receiving DFI funding being biased towards firms who have shown strong economic and employment growth in the past, the relationship is actually quite the opposite. Considering that the control group of NNM (*ISM*) exhibited -2.3% average annual employment growth, compared to 4.7% average annual employment growth of the unmatched control group, it seems that additional DFI funding was actually channeled more towards struggling firms or the firms with highest unexplored employment growth potential.

Comparing differences in average annual employment growth between treated and control firm-year observations using the Kernel matching procedure yields results of similar nature, but of smaller magnitude than with the NNM (*ISM*) method. Average annual employment effect of receiving additional DFI funding was 10.1% when using ISM propensity score estimates for matching of sample firms and 8.5% when using OSM propensity score estimates. In both cases, ATT is statistically significant at 10% confidence intervals. Key driver behind the smaller magnitude of ATT when compared to NNM (*ISM*) approach, is that the average annual employment growth for the control group using the Kernel matching method is much closer to average annual employment growth of the unmatched control group. Results of Kernel matching would thus suggest that even though characteristically similar sample firms to those who receive additional DFI funding exhibit positive average annual employment growth even without additional funding, their average annual employment growth is substantially boosted (by about 8.5% to 10.1%) by the act of funding. Also considering that the average annual employment growth for the entire firm sample is 8.5% and median annual employment growth is 5.7% (see Table 1, Section 4.2), the interpretation and magnitude of the results yielded using the Kernel matching method seem more plausible than for the NNM (*ISM*) method.

All in all, results of the treatment effects analysis provide strong grounds to believe that DFI funding has a statistically significant, positive effect on firm-level employment growth in DFI investments. Though NNM and Kernel approaches produce results of slightly differing magnitude and statistical significance, in both cases the average annual net employment growth for firms receiving additional DFI funding is higher and distinctly different from their control groups. Thus, hypothesis **H2$_a$** is accepted and null-hypothesis **H2$_0$** is rejected.

6.2.3 Sensitivity discussion and further robustness checks

First potential methodological robustness issue is encountered when examining the dispersion of propensity scores for the OSM approach, as described in Table 5 and shown in Figure 7 (see Section 6.2.2). Maximum propensity score for both treated and control firms across the entire sample is just slightly above 0.25, which indicates that specification (3), as defined in the previous section, only at best predicts with a 25% accuracy whether firm *i* will or will not receive a capital infusion at year *t*. This methodological limitation is primarily driven by a rather limited availability of different firm descriptive variables in the Finnfund dataset. As no other databases could be combined with the Finnfund dataset due to data consistency issues, a rather limited amount of firm descriptive variables could be used as explanatory variables in estimating the probability of firm receiving or not receiving a capital infusion during a given year. As discussed earlier (see Section 6.2.2), this methodological challenge is tackled by also using the ISM approach in propensity score estimation and subsequent propensity score matching (PSM).

Another typical criticism towards the PSM method, specifically related to panel data, is that unobservable time-varying characteristics might affect the outcome of a treatment effects analysis (Imai and Azam, 2012). However, considering that amongst sample firms there was no one fixed "treatment year" when sample firms might have or might not have received additional DFI funding, it seems justified to assume a random distribution of $capital\ infusion_{i,t}$ across time. Assuming a random distribution of $capital\ infusion_{i,t}$ across time allows to observe the effect of $capital\ infusion_{i,t}$ on the outcome variable ($g_{i,t}$) without worrying that potential, time-varying and unobservable characteristics of $capital\ infusion_{i,t}$ might have an effect on $g_{i,t}$.

However, even in the presence of such time-randomization of the "treatment variable" some studies might choose to perform alternative analyses to PSM as robustness checks of previous' findings. An approach typically used with panel data is a difference-in-difference propensity score matching (DID-PSM), as outlined for instance by Smith and Todd (2005) and Imai and Azam

(2012). Essentially, this method involves taking the first difference of the outcome variable from *t-1* to *t*, where treatment takes place at *t* for treated group and compare it with a first differenced outcome variable of a propensity score matched control observation, where the control has not received treatment at *t*.

This same analysis is performed below, but differently to the propensity score matching in Section 6.2, only first capital infusions received by sample firms are considered. This decision is made, because standard deviation of $g_{i,t}$ is significantly higher for firm-year observations during which sample firms receive additional DFI funding (see ***Table A-3***, **Appendix 2**). When differencing a growth variable (i.e. in this case, first difference of $g_{i,t}$ is the growth of net employment growth defined as $g_{i,t} - g_{i,t-1}$) extreme fluctuations of outcome variable can occur. Thus, in order to minimize the effect that increased volatility of $g_{i,t}$ which follows after receiving additional DFI funding, has on the observed differences in $g_{i,t} - g_{i,t-1}$ between treated and control firm-year observations, it seems most appropriate to examine the employment effect of only the first capital infusion received by a firm *i* during years 2008 to 2014.

Table 8 presents the results of DID-PSM analysis following approaches of Smith and Todd (2005) and Imai and Azam (2012). The analysis examines the effect of a first additional DFI funding round, potentially received by firm *i* during years 2008 to 2014, on average growth in annual employment growth of firm *i*. Matching is performed using nearest neighbor one-to-one matching.[22] Similarly to Section 6.2.2, test on balancing property of explanatory variables is performed and indicates no statistically significant difference for any of the explanatory variables between the treated and control firm-year observations (see ***Table A-4***, Appendix 2 for further details).

As can be clearly seen from Table 8, including only the first capital infusions received by a firm in the analysis significantly decreases the sample size of both treated and control firm-year observations. Taking the first difference of net employment growth also dramatically changes the nature of the outcome variable, as average growth of annual employment growth is negative both for the treated and the control group. While this result may seem surprising at first, considering the established negative relationship between firm size and employment growth, both in this study and

[22] Similarly as in Section 6.2.2, both NNM and Kernel matching was performed. However, due to high similar results and in order to keep the analysis concise, only NNM results are reported below.

in empirical literature more generally, the observed relationship becomes intuitive. If a firm experiences positive employment growth, as is the case with sample firms of this study on average, the pace of firm employment growth is bound to decrease over time as firm size increases.

Table 8. DID-PSM treatment effects analysis of first capital infusion effect

Analysis of average treatment effect (ATT) of additional DFI funding ($capital\ infusion_{i,t}$) on first difference of net employment growth ($g_{i,t} - g_{i,t-1}$). Results reported for unmatched and NN matched. For all groups, average treatment effects estimated using all available observations from all sample firms for the time period of 2008 to 2014.

	Mean ($g_{i,t}$-$g_{i,t-1}$)				***N(obs)***	
Matching algorithm	**Treated**	**Control**	**ATT**	**T-stat**	**Treated**	**Control**
Unmatched	-0.0184	-0.0673	0.0489	0.76	18	116
NNM (ISM)	-0.0181	-0.170	0.1516	1.07	16	105
NNM (OSM)	-0.0156	-0.2623	0.2467	1.34	17	108

Matching algorithm refers to the propensity score matching algorithm used for selection of *treated* and *control* group firm-year observations. *Treated* group reports average $g_{i,t}$ for firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014 and qualified for matching against a control group using the specified *matching algorithm*. *Control* group reports average $g_{i,t}$ for firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014 and are matched to *treated* group using the specified *matching algorithm*. *ATT* reports the difference in average $g_{i,t}$ between *treated* and *control* group, where firm-year observations are selected into both groups using the specified matching algorithm. *T-stat* reports the t-statistic of *ATT*. Statistical significance of coefficients is denoted as follows: *P < 0.1; **P < 0.05; ***P < 0.01

Interestingly, even though average growth of annual employment growth is negative across sample firms, additional DFI funding seems to have a positive effect on average $g_{i,t} - g_{i,t-1}$ for sample firms. This is indicated by a positive, if statistically insignificant, difference in average $g_{i,t} - g_{i,t-1}$ between treated and control firms (ATT) for both NNM approaches. Even though statistically insignificant, the observed positive difference in average $g_{i,t} - g_{i,t-1}$ between treated and control firm-year observations suggests that additional DFI funding is potentially capable of slowing down the decreasing pace of annual employment growth for sample firms - and as indicated by the magnitude of the difference, at a potentially quite substantial pace. Statistical insignificance of the ATT is highly likely attributable to the small sample size of the DID-PSM analysis. The sample size is limited primarily by the small number of employment growth observations available for sample firms before receiving their first capital infusion. Taking the first difference of the limited number of such outcome variable observations then further decreased the sample size.

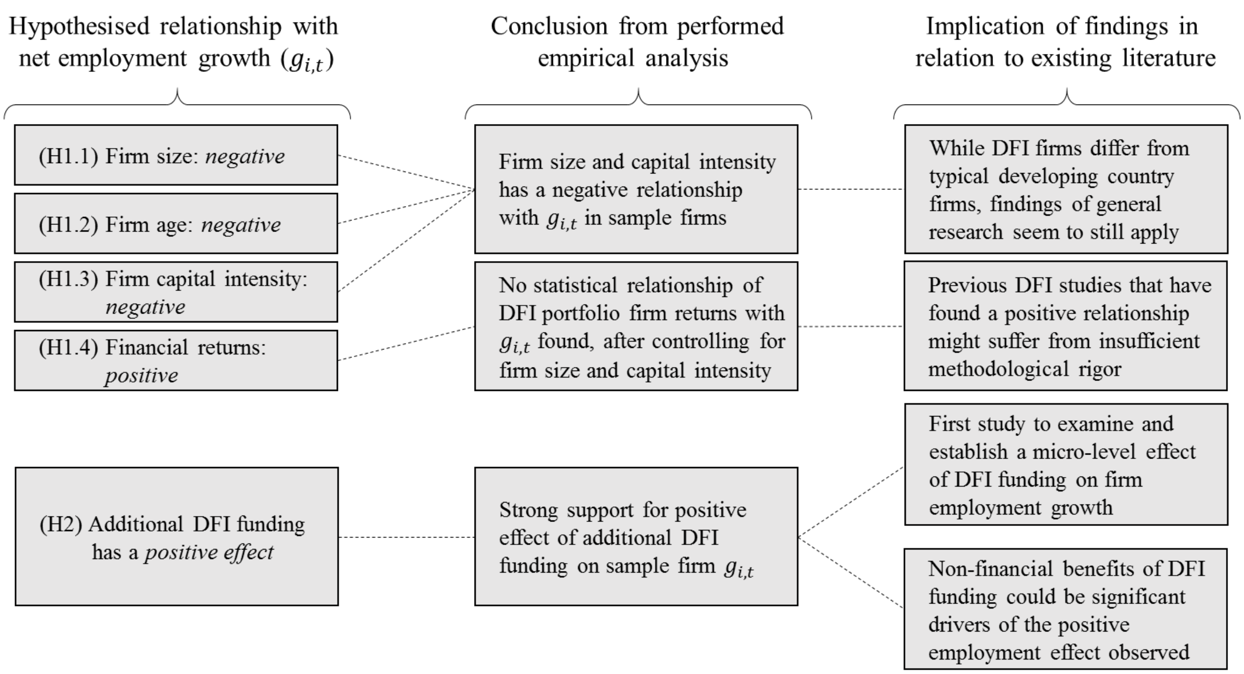
To sum up, it is difficult to draw explicit conclusions from the DID-PSM analysis performed following Imai and Azam (2012) on how first instances of additional DFI funding effect growth of sample firm annual employment growth ($g_{i,t} - g_{i,t-1}$). Even though observed differences between treated and matched control observations indicate on DFI funding having a positive effect on the otherwise decreasing average pace of annual employment growth of sample firms, the sample available for the analysis is small and observed differences statistically insignificant.

7. Conclusion and discussion

7.1 General findings

The aim of this study was to gain a better understanding on the job creation dynamics that occur in investee firms of development finance institutions. More specifically, the goal was to examine how investment-level characteristics of DFI investments, such as firm size, firm age, firm capital intensity and investment returns are related to job creation of these investments. In addition, the effect of DFI funding itself on firm-level employment growth was studied, by comparing average employment growth of DFI investee firms receiving additional DFI funding to employment growth of matched DFI investee firms not receiving additional funding. With regards to this, the study has established several interesting results both in context of firm-level job creation and general DFI-related literature. The key conclusions from the empirical results of the study and their implications are summarized in ***Figure 8***.

Figure 8. Summary of key conclusions and research implications based on the empirical results of the study



Firstly, examining firm-level determinants of employment growth in DFI portfolio firms, a negative relationship for both firm size and capital intensity with firm-level employment growth in DFI investments is established. Both relationships are economically meaningful and in line with theoretical and empirical literature on firm-level employment growth determinants, but have not been previously tested with a sample of DFI portfolio companies. For instance, Davis et al. (1996), Neumark et al. (2011), Haltiwanger et al. (2013), Rijkers et al. (2014) and Ayyagri et al. (2016) establish a negative relationship between firm size and employment growth in both developed and developing countries. A negative relationship between firm capital intensity and employment growth is on the other hand predicted by the capital-labor substitution relationship of the basic Cobb-Douglas production function (Cobb and Douglas, 1928). However, unlike Haltiwanger et al. (2013) or Rijkers et al. (2014), no statistically significant relationship between firm age and employment growth is found in this paper. While this might suggest that firm age is not a significant determinant of employment growth for sample DFI investee firms, the observed statistical insignificance is most likely related to the problematic firm age proxy used in this paper.

More interestingly, this paper finds no statistically significant relationship between returns of DFI investments and their firm-level employment growth, after controlling for firm size and capital intensity. This parts from previous findings of DFI practitioner literature, which not controlling for these well-established firm-level employment growth determinants has found a positive relationship between returns from DFI investments and investment-level job creation (Wilton and Allen, 2012). Considering that the empirical work in this study follows closely some of the most recent methodological approaches outlined in studying firm-level employment growth determinants, i.e. Haltiwanger et al. (2013) and Rijkers et al. (2014), the results provide strong grounds to question the findings of Wilton and Allen (2012). As the existence of a positive link between returns from DFI investments and investment-level job creation seems to have established itself as a widely accepted truth in discussion surrounding the DFI industry, findings of this paper have significant importance. It is however worth noting, that as the results are observed from financial returns of sample DFI investments and not from firm-level profitability directly, results of this paper do not allow to make any explicit conclusions on the potential relationship between firm-level profitability and firm-level employment growth in DFI investments.

Secondly, additional DFI funding is found to positively and statistically significantly effect firm-level employment growth in sample firms. By matching 96 Finnfund investments that received additional funding during the years 2008 to 2014 with a group of control investments not receiving additional funding through a PSM procedure, a statistically positive effect of additional funding on average annual employment growth is established. This is the first paper to document such a micro-level relationship between DFI funding and firm-level job creation.

The employment effect of DFI funding is examined, by matching firm-year observations during which a sample firm received funding, against control observations where sample firm has otherwise similar firm characteristics to the funded firm, but does not receive funding during the given year. Matching is performed based on sample firm propensity scores, which are estimated using two different approaches and are subsequently matched using two different matching algorithms; nearest neighbor one-to-one matching (NNM) and Kernel matching. The statistical significance of the employment effect of DFI funding persists across all methodologies, apart from the case of NNM using *out-of-sample* estimated propensity scores. Also, while the performed robustness check using a DID-PSM approach following Imai and Azam (2012) yields somewhat inconclusive results, the general trend in direction and magnitude of the results observed across all the methodologies strongly suggests that additional DFI funding has a positive effect on firm-level job creation. Considering these empirical findings in parallel to financial and non-financial benefits associated with DFI funding, as proposed by both DFI literature (e.g. Kingombe et al., 2011, te Velde and Massa, 2011 and Joujean and te Velde, 2013) and by applicable VC literature (e.g. Large and Muegge, 2008 and Balboa et al. 2011), there are also good theoretical grounds to believe that DFI funding has a beneficial effect on firm-level employment growth. Lastly, if one assumes that comparing the employment effect of additional DFI funding against characteristically similar non-funded DFI investments is similar to examining the firm-level employment effect of DFI funding more generally, findings of this paper can to some extent be generalized to consider the employment effect of DFI funding on firms previously not backed by DFIs.

While the study design does not allow to examine separately whether financial or non-financial benefits affect the firm-level employment growth of sample firms, some speculation can still be made. One exciting characteristic of the results from the DFI funding effect analysis is that additional DFI funding is found to increase employment growth rate (%), not merely the absolute number of jobs.[23] As both this paper and previous literature on employment growth determinants have established a negative relationship between firm size and employment growth, finding a positive effect of funding on employment growth rate (%) provides a strong argument against the

[23] The outcome variable for all regressions examining employment growth, apart from the DID-PSM analysis, is net employment growth (%) as defined by $g_{i,t}$ - not the change in absolute number of employees (#).

intuition that purely expansionary activity of the firm, due to availability of new financial capital, could increase the rate at which a firm creates jobs. In other words, because rate of employment growth should slow down as firm grows, DFI funding is highly likely to increase employment growth of investee firms through some other channel than purely provision of additional financial resources for firm growth. This insight is also supported by the results of DID-PSM analysis, which shows a positive effect of additional DFI funding on the growth of average employment growth.

Also, as the effect of DFI funding is studied on net employment growth of the same year *t*, it seems likely that a significant part of the effect could be driven by non-financial benefits of DFI funding. Recruitment and firm expansion are known to be time consuming processes and considering that the additional funding is not necessarily occurring at the start of year *t*, this would leave sample firms with rather short time to expand purely on the basis of received new capital. A more likely explanation is that a DFI is paying higher attention already before year *t* to investee firms that are candidates for additional funding and is providing managerial guidance and technical assistance to such firms. Thus at year *t*, when a decision on providing additional funding is made, firms who end up getting funded are already in good shape and growing due to DFI non-financial services received prior to year *t*. This makes some of the exhibited employment growth at year *t* traceable to the non-financial benefits received prior to year *t* and explains the "quickness" of the effect of additional DFI funding on firm employment growth. To summarize, it seems likely that a significant part of the employment effect of DFI funding is driven by non-financial benefits of DFI funding, because the employment effect is observable so quickly in sample firms.

7.2 Suggestions for further research

Considering that empirical literature documents a wide range of firm-level employment determinants, very few of which have been examined in context of DFI investments, there are numerous interesting opportunities for further research. Veldhuis et al. (2013) provide an excellent review of recent research on firm-level employment growth determinants, documenting several empirical studies establishing links between e.g. firm export orientation and innovation ability and firm employment growth. Studying how these relationships hold in the context of DFI investee firms would significantly increase our knowledge of the job creation dynamics in DFI investments.

With regards to the effect of DFI funding on firm-level employment growth, it would be exciting to see a study that examines employment growth of DFI backed firms against a matched group of control firms that have never received DFI investments. Such analysis would provide significantly stronger grounds to conclude, whether a positive employment effect of DFI funding exists also outside the context of DFI investee firms, in the general firm population.

Lastly, a study examining separately how the financial and non-financial benefits of DFI backing potentially affect employment growth would lead to a far better understanding of the mechanisms underlying the causality established in this paper. Such research could be performed in similar manner to e.g. Jääskeläinen (2006) and Balboa et al. (2011), who look at how the total number of portfolio companies managed by a VC investment manager relates to the performance of portfolio companies under his or her management. In this case, the number of portfolio companies per investment manager acts as a proxy for investment manager's attention and thus for the amount of non-financial benefits provided by the VC, allowing to examine the effect of non-financial benefits directly.

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A. Appendices

Appendix 1.

Table A-1

Results of logit regression of $capital\ infusion_{i,t}$ on firm size, age of investment, 1 year lagged log *GDP*,1 year lagged *GDP* growth and all sector dummies. Reported coefficients are in terms of log odds. Regression is executed on all sample firms with available data and on the time period from 2008 to 2014.

	In-sample model			
	(1)	**(2)**	**(3)**	**(4)**
Firm size	**-0.00074****	**-0.00080*****	**-0.00089*****	**-0.00085*****
	(-2.45)	**(-2.63)**	**(-2.84)**	**(-2.74)**
Age of investment	**-0.503*****	**-0.509*****	**-0.516*****	**-0.565*****
	(-5.58)	**(-5.59)**	**(-5.65)**	**(-5.65)**
1-yr lag log GDP	**0.438*****	**0.383*****	**0.425*****	**0.457*****
	(2.94)	**(2.57)**	**(2.91)**	**(3.11)**
1-yr lag GDP *g*	**8.015***	**8.825***	**7.866***	**7.412**
	(1.72)	**(1.90)**	**(1.71)**	**(1.60)**
Firm Sector				
Financial	**-0.697***			
	(-1.91)			
Infrastructure		**0.704*****		
		(2.66)		
Manuf & Serv			**-0.478***	
			(-1.94)	
Agribusiness				0.468
				(1.43)
Constant	-3.224**	-3.104**	-2.950**	-3.461***
	(-2.46)	(-2.41)	(-2.28)	(-2.69)
N (obs)	448	448	448	448
LR chi-squared	70.06***	73.04***	69.86***	68.03***
Pseudo R-squared	0.1362	0.1419	0.1358	0.1322

All specified regression equations are computed as logit regressions. Dependent variable for all specifications is a dummy variable $capital\ infusion_{i,t}$, where $capital\ infusion_{i,t}$ is assigned a value of *1* for firm *i* at year *t*, if change in *firm total investment* for firm *i* from year *t-1* to year *t* is greater than 0 and is assigned a value of *0* otherwise. $Firm\ size_{i,t}$ is defined as the number of employees for firm *i* at year *t. Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i, i.e.* year *t – n. 1-yr* $lagged\ log\ GDP_{j,t}$ is the natural logarithm of GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t-1*. *1-yr* $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{\mathrm{j},t-1}}{\mathrm{GDP}_{\mathrm{j},t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t.* $Financial_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the financial sector and *0* otherwise. $Infrastructure_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the infrastructure or utilities sector and *0* otherwise. $Manuf$ & $Serv_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the manufacturing or services sector and *0* otherwise. $Agribusiness_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the agribusiness sector and *0* otherwise.LR chi-squared refers to likelihood-ratio (LR) chi-square test statistic, which is a test on joint statistical significance of regression coefficients. Pseudo R-squared refers to McFadden pseudo R-squared. Statistical significance of coefficients is denoted as follows:

*P < 0.1; **P < 0.05; ***P < 0.01.

Table A-2

Results of logit regression of $capital\ infusion_{i,t}$ on firm size, age of investment, 1 year lagged log *GDP*,1 year lagged *GDP* growth and all sector dummies. Reported coefficients are in terms of log odds. Regression is executed for firms receiving a capital infusion using only observations from years prior to the year when they received their first capital infusion and for firms not receiving a capital infusion on the time period from 2008 to 2014.

	Out-of-sample model			
	(5)	**(6)**	**(7)**	**(8)**
Firm size	**-0.00082**** **(-1.96)**	**-0.00082**** **(-2.04)**	**-0.00082**** **(-2.04)**	**-0.00093**** **(-2.18)**
Age of investment	-0.117 (-1.15)	-0.117 (-1.15)	-0.119 (-1.17)	-0.121 (-1.16)
1-yr lag log GDP	0.0014 (0.01)	0.046 (0.19)	0.049 (0.20)	-0.056 (-0.22)
1-yr lag GDP *g*	-3.974 (-0.56)	-5.160 (-0.74)	-6.113 (-0.90)	-7.528 (-1.10)
Firm Sector				
Financial	**-1.062*** **(-1.86)**			
Infrastructure		0.250 (0.55)		
Manuf & Serv			0.067 (0.18)	
Agribusiness				0.796 (1.52)
Constant	-0.540 (-0.25)	-1.065 (-0.52)	-1.012 (-0.49)	-0.188 (-0.09)
N (obs)	227	227	227	227
LR chi-squared	14.38**	10.47*	10.21*	12.36**
Pseudo R-squared	0.0712	0.0519	0.0506	0.0612

All specified regression equations are computed as logit regressions. Dependent variable for all specifications is a dummy variable $capital\ infusion_{i,t}$, where $capital\ infusion_{i,t}$ is assigned a value of *1* for firm *i* at year *t*, if change in *firm total investment* for firm *i* from year *t-1* to year *t* is greater than 0 and is assigned a value of *0* otherwise. $Firm\ size_{i,t}$ is defined as the number of employees for firm *i* at year *t*. *Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i, i.e.* year *t – n. 1-yr* $lagged\ log\ GDP_{j,t}$ is the natural logarithm of GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t-1*. *1-yr* $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{j,t-1}}{\mathrm{GDP}_{j,t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of firm domicile country j for firm *i* at year *t.* $Financial_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the financial sector and *0* otherwise. $Infrastructure_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the infrastructure or utilities sector and *0* otherwise. $Manuf\ \&\ Serv_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the manufacturing or services sector and *0* otherwise. $Agribusiness_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the agribusiness sector and *0* otherwise.LR chi-squared refers to likelihood-ratio (LR) chi-square test statistic, which is a test on joint statistical significance of regression coefficients. Pseudo R-squared refers to McFadden pseudo R-squared. Statistical significance of coefficients is denoted as follows:

*P < 0.1; **P < 0.05; ***P < 0.01.

Appendix 2.

Table A-3

Summary statistics on net employment growth ($g_{i,t}$) for firm-year observations during which sample firm receiving additional DFI funding (treated group) and for firm-year observations during which sample firm did not receive additional DFI (control group). Statistics reported for all sample firms with available data and for years 2008 to 2014.

	Firm-years w/ additional DFI funding (treated)				Firm-years w/o additional DFI funding (control)			
	N (obs)	***Mean***	***Median***	***St. Dev***	***N (obs)***	***Mean***	***Median***	***St. Dev***
Net employment growth (%)	127	13.6%	6.8%	49.0%	355	4.7%	4.2%	36.6%

Table A-4

Balancing test on explanatory variables for DID-PSM analysis. *Treated* group includes firm-year observations of sample firms that received additional DFI funding during the time period of 2008 to 2014 and qualified for matching against a control group using the specified *matching algorithm*. *Control* includes firm-year observations of sample firms that did not receive additional DFI funding during 2008 to 2014 and are matched to *treated* group using the specified *matching algorithm*.

	Mean		
	Treated	**Control**	**T-stat**
NNM (ISM)			
Firm size	337.19	466.25	-0.66
Age of investment	3.25	3.13	0.31
1-yr lag GDP	7.81	7.98	-0.64
1-yr lag GDP *g*	5.19%	4.69%	0.66
Firm sector (financial)	0.16	0.16	0.00
NNM (OSM)			
Firm size	365.24	444.18	-0.41
Firm sector (financial)	0.06	0.0	1.00

$Firm\ size_{i,t}$ is defined as the number of employees for firm *i* at year *t*. *Age of investment* is defined as the difference between the *current year*, i.e. year *t* for firm *i* and the year of initial DFI investment into firm *i*, *i.e.* year *t – n*. *1-yr* $lagged\ log\ GDP_{j,t}$ is the natural logarithm of GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t-1*. *1-yr* $lagged\ GDP\ growth_{j,t}$ is defined as $\Delta 1yr\ lagged\ GDP_{j,t} = \frac{\mathrm{GDP}_{j,t-1}}{\mathrm{GDP}_{j,t-2}} - 1$, where $GDP_{j,t}$ is the GDP (in nominal US$) of firm domicile country *j* for firm *i* at year *t*. $Financial_i$ is a dummy variable assigned a value of *1* if firm *i* belongs to the financial sector and *0* otherwise. Statistical significance of coefficients is denoted as follows: *P < 0.1; **P < 0.05; ***P < 0.01.